Sources and practicality of momentum profits: evidence from the UK market

Badreddine, Sina

SOURCES AND PRACTICALITY OF MOMENTUM PROFITS: EVIDENCE FROM THE UK MARKET

A THESIS SUBMITTED FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

SINA BADREDDINE

DURHAM BUSINESS SCHOOL, DURHAM UNIVERSITY

August 2009

To my Mum and Dad,
Shafika and Hassib

Acknowledgments

This thesis is the work of years of research that I have spent at Durham University. During that time, a number of people have contributed in various ways to the making of this thesis. Therefore, and with great gratitude, their names and help are mentioned.

In the first place, I would like to convey my gratitude to Professor Phil Holmes for his supervision, advice and guidance throughout the whole journey of my PhD studies. I can confidently admit that without him, this work would not have been possible. I have learned much from his insights into research planning and conduction. His reassurance had been always vital and his patience is appreciated.

I am also indebted to Dr Emilios Galariotis for his supervision, advice and exceptional concern to the progress of my studies. His critical comments are most valuable knowing that he was giving much of his precious time to read my work and discuss it with me. I am glad to have Dr Galariotis as my supervisor who has enriched my knowledge with great ideas.

I am grateful to Dr Joseph Cassidy, the Principal of St. Chad's College, for his assistance in obtaining a financial grant at a crucial time of my studies. I would also like to thank the staff of St Chad's College for their support since the first day I arrived to Durham and special thanks goes to Susan Mather.

I am also grateful to my colleagues Dr Vasilis Kalliderakis, Dr Diana Abu Ghunmi and Mohammad El-Tayeh for sharing their thoughts and ideas with me. I would also like to acknowledge Dermot McGrath from the FT Research Centre for his help in obtaining the FTSE All Share Historical Constituents that were used in this thesis. I also benefited from the support of Durham Business School and Professor Krishna Paudyal to obtain funding for the research. I also owe many thanks to Bilal Ballout for his assistance in the matching process of the data sample.

I would also like to thank Dr Zichao Zhang and Dr Konstantinos Kassimatis for their comments and who have agreed to carry out the viva at a short notice.

Many thanks go to the staff of Durham Business School and especially to Patricia Linford and Andrea Bailey from the Doctoral Office and Dr Rebecca Stratling. I would also like to thank my colleagues at the Open-Access Centre and in particular Mary Fender.

I am also fortunate for the great friendship of Raid Khayyat, Aissa Yahiaoui, Sunan Rustam, Michael Lamb and Suhrab Abbasi.

I am also indebted to Una McGahern who has proofread the thesis and who has been very supportive and caring.

Finally, my deepest thanks and gratitude go to my mum and dad who have sacrificed a lot for my sake and to my sisters and brother Linda, Zeina and Hasan and to my sister-in-law Diala.

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Abstract

It is hard to believe that rewarding opportunities in a liberalised market are left unexploited by acquisitive market participants or even by proficient institutional investors. Notwithstanding this, the sources of momentum profits have been puzzling academics for many years. Therefore, the incentives for these rewarding opportunities remain an unresolved mystery long after the momentum phenomenon has been identified. The significance of the momentum phenomenon is reflected in the voluminous studies that investigate it.

This thesis aims to investigate a number of issues surrounding the debate on the momentum phenomenon in order to provide a broader understanding of the profitability of momentum strategies and its sources by using alternative as well as some new methods. Furthermore, this study investigates momentum strategies in the UK market by controlling for several market microstructure effects and finds that momentum profits tend to disappear after the six months holding period, from the year 2000, providing evidence of fading momentum profits. While market states fail to explain fading momentum profits, this study argues that it is the result of gradual market awareness. Seasonal effects on momentum returns after 1998 show evidence of continuing tax-loss selling activity, and hence, draw implications on the effectiveness of the governmental 1998 Tax-Act. This thesis also supports the presence of an industry effect on the cross-section of momentum returns; however, this effect is small and is confined to the stocks that have performed well in the past and increases with liquidity. Empirical evidence suggests that momentum profits exist among the highly liquid stocks that are weekly traded. The findings also suggest that market frictions such as short sales constraints and trading costs cannot eliminate momentum profits among optioned or non-optioned (comparable) stocks using a new technique to measure transaction costs. The overall evidence implies that the observed momentum profits are not fully attributed to the argued trading obstacles but mainly driven by biased investment decisions and that momentum profits are significant even after controlling for uncertainty, ambiguity and trading costs.

1 Chapter One: Introduction

1.1 Overview

The capability of predicting future profits based on past news is the core concept of momentum strategies. Particularly, to take advantage of predicting that a group of stocks will outperform another group of stocks entails a long position in the former offset by an equivalent short position in the latter to earn an abnormal return that is equal to the difference in the performance – return – of the two groups. Ideally, there is no investment embedded in such a strategy as the short position finances the long position resulting in a zero-cost portfolio. The anticipation of future momentum profits that is based on past stock returns is known as price momentum, or relative strength strategies. Jegadeesh and Titman (1993) were the first to document the profitability of momentum strategies. However, the literature identifies other forms of momentum such as earnings momentum, industry momentum, style momentum and 52 week high price momentum[1].

After Jegadeesh and Titman (1993) (JT, hereafter) documented in their seminal paper the existence of momentum profits in the US market, many studies have shown that the momentum profits have persisted since their discovery. Unlike other acknowledged stock return anomalies that tend to disappear a while after being discovered, evidence on the momentum anomaly remains significant more than a decade after being identified. JT (1993) find that holding over 3 to 12 months, stocks that performed well over the past 3 to 12 months deliver higher returns than stocks that performed poorly over the same prior period. Winner stocks outperform the loser stocks by a monthly average return of 1% over the 12 months holding period. In their study, JT show that the observed momentum profits are not confined to small or high beta stocks that are argued to have higher risk and larger expected returns. In fact, they show that portfolios of large stocks, as well as portfolios of low beta stocks, generate significant momentum profits. After decomposing momentum profits, JT argue that they are mainly related to market underreaction to firm-specific information.

[1] See for example, Chan et al. (1996), Moskowitz and Grinblatt (1999), Pan et al. (2004), Chen and De Bondt (2004) and George and Hwang (2004).

Regarding the UK market that is the focal point of this study, there is existing literature on momentum profitability that the thesis considers. UK momentum studies show that momentum strategies are as significantly profitable as those in the US market. However, many of the issues raised in relation to the above profitability have not yet been investigated for the UK market and there remain gaps which require further investigation. More research is required for an out-of-sample market to substantiate earlier findings in the literature regarding the sources of momentum. The empirical chapters review these studies and their results in relation to the raised research questions.

In order to earn momentum profits, it is possible to argue that past information employed in such strategies is not fully incorporated into current prices. This challenges even the weakest form of market efficiency[2]. In the absence of limits to arbitrage, if it is possible to make profits simply by looking at past prices, astute investors should take corresponding investment decisions to exploit the rewarding opportunities leading to the elimination of momentum profits. Thus, finding evidence of the continuation of momentum profits questions investors' ability to eliminate them. Empirical evidence from the literature supports the existence and continuation of momentum profits in major international stock markets which validates the effectiveness of technical analysis strategies. Why is it then that market participants are not exploiting past patterns to make profit? There have been several attempts to explain the reluctance of investors to exploit momentum profits. Some evidence from the US suggests that momentum profits are not robust to trading costs while other evidence suggests that investors fail to act rationally and underreact to information. While the ongoing debate is mainly focused on evidence from the US market, evidence of the practicality of momentum strategies in the UK market is lacking and insufficient.

Therefore, this thesis aims to undertake a thorough investigation of momentum strategies and their profitability by focusing on the UK market. The choice of the UK

[2] The literature identifies three levels of market efficiency: The weak-form states that all past market information are fully reflected in securities prices. In other words, using technical analysis to achieve abnormal gains is of no use. The semi-strong form asserts that all publicly available information is fully reflected in securities prices. In other words, using fundamental analysis as an investment strategy cannot be a successfully consistent investment strategy. The strong-form asserts that all information, public or private, is fully reflected in securities prices. In other words, even using insider information is of no use. See Fama (1970, 1991) for more on market efficiency and the testing of the Efficient Market Hypothesis.

market provides a useful out-of-sample test for the findings based on extensive US momentum studies. In addition, this thesis uses new estimation methods and provides some novel findings which contribute to the literature. First, this thesis examines the persistence of the momentum anomaly after its discovery, and provides new evidence of seasonal and market states effects on UK momentum returns. The thesis also addresses the impact of market-wide and firm-specific components on momentum returns and provides new evidence on the role of each. In particular, the thesis examines the effects of industry and idiosyncratic volatilities on the cross-section of momentum returns. Furthermore, this thesis questions whether market underreaction to news is attributed to trading obstacles or to investors' behaviour by examining momentum strategies on optioned stocks which are argued to suffer the least from short sales constraints and information ambiguity. The thesis investigates the robustness of momentum returns to trading costs and offers a new approach for measuring trading costs. The restriction of using highly liquid stocks, in some cases, and optioned stocks to estimate momentum profits and to investigate the sources of momentum, has important implications for market traders and provides a test of the practicality of momentum profits.

The next section provides a brief review of the various approaches used to explain momentum profits and the persistence of the momentum anomaly. The thesis categorises them according to three research strands which are discussed below.

1.2 Fundamental strands regarding research on momentum strategies

Investigating the momentum phenomenon is addressed in several strands in the finance literature. One tenet of the literature argues that if returns were appropriately adjusted for systematic risk, then momentum profits would disappear, i.e., momentum returns are not abnormal and, consistent with neoclassical finance, they are commensurate with the risk of the investment. An alternative view in the literature rationalises the persistence of momentum profits by showing that trading barriers prevent market traders from exploiting the profits. Others argue that the incentives for these profits are related to irrational trading decisions caused by systematic bias in investors' behaviour. The three approaches are briefly reviewed below before it is shown how this thesis corresponds and contributes to the literature.

In the first strand, stock prices are deemed to follow a random walk. Samuelson (1965) finds random walk characteristics for stock prices movements, and deduces that the exhibited random walk of stock prices is a result of a competitive market where information is immediately incorporated. Using empirical evidence, Fama (1970) concludes that stock prices cannot be predicted from past prices alone and that technical analysis is not, therefore, a basis for investment strategies. Instead, he proposes to test the Efficient Market Hypothesis (EMH, hereafter). The efficient market theory claims that prices adjust instantaneously to the arrival of news, which in turn are assumed to follow a random walk. The randomness in the movement of stock prices eradicates the potential for return predictability. In relation to momentum profits, investors would not be able to earn any abnormal return if prices follow a random walk. The efficient market theory further assumes that investors are Bayes rational and have homogeneous beliefs and sensible preferences. Since the efficient market theory assumes efficient prices then it requires the availability of a model that can estimate the expected return and the price of the security. If the estimated price is not different from the current price, then the asset pricing model is the appropriate model and prices are also efficient. Fama (1970, 1991) posits that the main issue that needs to be addressed is the joint-hypothesis problem which states that *"(market efficiency)...must be tested jointly with some model of equilibrium, an asset pricing model"* (Fama, 1991, p. 1576). In other words, what is needed is a model that can determine the stock price correctly, which in turn provides a basis for testing evidence of market efficiency.

Many attempts to explain momentum profits by an asset pricing model have failed, including the Fama-French 3 factor model (Fama and French, 1996). Fama (1998) states that *"the problem is that all models for expected returns are incomplete descriptions of the systematic patterns in average returns during any sample period. As a result, tests of efficiency are always contaminated by a bad-model problem"* (p. 291). Other attempts use different approaches. Conrad and Kaul (1998) argue that momentum profits result from the cross-section of stock returns. However, JT (2002) show that the Conrad and Kaul results are biased towards the small sample and that cross-sectional variation in unconditional expected returns is small relative to the time-series variation in realised returns. Conditioning on expected dividend growth rates over time, Johnson (2002) finds that recent performance is correlated with growth rates which, in turn, is monotonically related to risk and may account for some of the momentum anomaly; whereas Berk et al. (1999) build a model that conditions on the expected cash flows which they relate to changes in risk over time. Their model suggests contrarian rather than momentum profits at short horizons.

The second strand provides evidence that market frictions prevent investors from correcting any mispricing; the latter, eventually, results in the form of autocorrelation in stock returns which induces momentum profits. The concept here is that prices are not updated instantaneously after news arrival because the costs embedded in trading the stock are higher than the change in the value that is suggested by the news signal. Hence, informed investors do not take action in response to the news unless the marginal profit exceeds the trading costs. In relation to the momentum strategy that involves short selling past losers, trading obstacles include short sales constraints and short sales costs on top of other trading costs. Lesmond et al. (2004) find that momentum profits do not exceed trading costs while Korajczyk and Sadka (2004) show that momentum profits are robust to bid-ask spread costs but fade after controlling for the price impact costs.. On the other hand, there is growing empirical evidence of short selling which suggests that short sale constraints and short sale costs are high for small and illiquid stocks (Ali and Trombley, 2006; D' Avolio, 2002; Nagel, 2005). However, these studies find marginal effect of short sale costs on large cap stocks, while Geczy et al. (2002) show that it is possible to earn from short selling.

In the efficient market theory, investors are likely to be rational[3]. As put by Barberis and Thaler (2003) "*first, when they (investors) receive new information, agents update their beliefs correctly, in the manner described by Bayes' law. Second, given their beliefs, agents make choices that are normatively acceptable, in the sense that they are consistent with Savage's notion of Subjective Expected Utility*" (p. 1053). Relaxing one or both assumptions suggests that investors are not fully rational. The final strand of research, known as behavioural finance, assumes that investors are biased in their perception and decision making (choice) processes. Thus, behavioural finance challenges one major pillar of the efficient market theory.

[3] Investors need not be rational for markets to be efficient as it is possible, although unlikely, that irrational investors will be irrational in different ways and thus in aggregate lead to markets being efficient

Experimental research in behavioural finance has led to an advanced understanding of the systematic biases that affect the investors' behaviour who are considered either bounded rational or irrational investors. Based on experimental studies in cognitive psychology, researchers have identified various cognitive biases that are adopted by financial economists to explain how investors perceive news or form their beliefs. Essentially, investors receive different news, interpret it differently and make different choices [4]. This heterogeneity in response to news, leads to what is known as underreaction or overreaction to news. Some studies attempt to build behavioural models that can explain the observed under- and overreaction in returns (see for example Daniel et al., 1998; Barberis et al., 1998; Grinblatt and Han 2005; Hong and Stein, 1999). Behavioural finance also notes that the existence of rational investors in the market does not eliminate the mispricing caused by irrational investors due to the limits of arbitrage (See Shleifer and Vishny, 1997). Rational arbitrageurs may find themselves powerless to correct the mispricing, which explains the continuation of return anomalies, specifically momentum. Therefore, while opportunities might not be rewarding, this does not imply that prices are efficient and so is the market.

1.3 Motivation of the thesis

The above strands of research show the different attempts to encompass momentum profits within their understanding of the sources of the anomaly. Studies which state that abnormal returns should not be predicted attempt to attribute momentum profits to various risk factors, such as: size, book-to-market, macro-economic variables, expected cash flow, revenue growth etc[5]. Studies that look at the robustness of momentum profits to trading costs also come to different conclusions. And finally, behavioural studies are bounded by the bias(es) put forward to explain the return anomaly ignoring other behavioural phenomena that may also be responsible for the anomaly but are not included in the proposed model(s).

[4] See more on this in Kahneman and Tversky (1982)

[5] See for example, Fama and French (1996), Chordia and Shivakumar (2002), Avramov and Chordia (2006), Griffin et al. (2003), Berk et al. (1999), Sagi and Seasholes (2007) and Johnson (2002).

Overall, the literature seems to contain several points of disagreement that the thesis investigates and aims to resolve. First, to the author's knowledge, there has not been any study to date that compares momentum profits before and after the discovery of the momentum anomaly in the UK market. Although momentum profits are found to exist in the UK, consistent with the evidence from the US, the disappearance of the anomaly need not occur at the same time in both markets. This is based on evidence that anomalies do not disappear simultaneously across markets. For instance, the January effect seemed to disappear in UK after the 1998 Tax Act but persisted in the US[6]; while the size anomaly seems to have followed the same paths in both markets and to have lessened and sometimes reversed[7]. Momentum profits were first documented in 1993 (JT, 1993) for the US market and in 1999 (Liu et al., 1999) for the UK market. Henker et al. (2006) find that momentum profits tend to vanish during 2001–2004 for the US market and they relate this to bad market states during that period. This raises concerns whether the momentum effect has started to disappear in the UK as in the US – across all markets – since 2001, or whether the momentum anomaly in the UK has begun to disappear since its discovery in the UK market in 1999. Given the evidence that anomalies might or might not disappear simultaneously across markets, the persistence of the momentum effect in the UK market is put under investigation.

Second, there has been evidence on the replacement of the January effect by an April effect in the UK market after the 1998 tax reform. The implication of this on momentum profits, however, has not yet been examined. This thesis aims to fill that gap in order to provide a recent affirmation on the profitability of momentum strategies in relation to seasonal effects.

Third, an ongoing debate on whether firm-specific components or market-wide components drive momentum returns raises concerns about the sources of momentum profits. Studies that examine momentum in industry sectors and mutual funds find strong support for the impact of market-wide information on momentum returns. On the other hand, there is a strand of research suggesting that momentum returns arise from stock returns autocorrelation that depends heavily on the situation of the firm or an event that takes place at some time. The latter suggestion associates the cross-section in

[6]For more details on this, see section 2.2.3.3 of chapter 2.
[7]See Horowitz et al. (2000) for the US market and Dimson and Marsh (1997) for the UK market.

momentum returns to firm-specific components. Undoubtedly, this area requires attention and still needs further investigation. While both industry sectors and firm-specific components seem to predict future returns, previous studies has shown that the volatility of the stock which contains industry and firm components can partially explain the cross-section in momentum returns. This thesis puts a step on the road by examining the role of each of the industry and firm-specific components of the stock volatility in explaining momentum returns.

Fourth, the advocates of the behavioural finance theory relate the observed mispricing to the biased behaviour of irrational investors which could not be corrected by arbitrageurs. While supporters of the efficient market theory believe that mispricing might occur, they claim that rational arbitrageurs should be able to detect and eliminate the mispricing. However, Shiller (1984) and Summers (1986) argue that, even if the mispricing is large and persistent, it is unlikely to be detected. Failing to detect price inefficiency might play a major role in explaining why the market can not predict the continuation of abnormal returns, such as momentum, and hence eliminate them. However, acquiring news is easier for some stocks than for other stocks. In other words, predicting future returns of stocks whose news are widely spread should allow investors to detect mispricing within these stocks at an early stage. To the author's knowledge, there has not been a momentum study in the literature of finance that focuses only on a sample of stocks that are characterised by a high level news availability about the value of the firm. This allows us to see whether the reluctance of intervening to correct mispricing – having controlled for the failure of detecting mispricing – is enough to drive momentum profits, regardless of the reasons and obstacles that prohibit arbitrageurs from intervention. This matter is approached by focusing only on optioned stocks versus control samples of the largest, mostly traded and most liquid stocks.

Fifth, the argument in the above paragraph on efficient market theory leads us to the following issue. Particularly, the question of whether rational arbitrageurs are capable of eliminating mispricing if detected is examined by testing the robustness of momentum profits against trading costs. Although this issue has been examined before, the robustness of momentum profits has not been tested on a sample of stocks that do not suffer from large transaction costs, large costs for searching and finding about a mispricing, or large short selling costs and constraints.

1.4 Contribution of the thesis

By undertaking a wide-ranging empirical analysis, this thesis adds to our understanding of issues surrounding momentum by making a number of important contributions. The above highlighted literature suggests disputes in the identification of the sources to momentum returns. Having been discovered for over a decade in the US market and over five years in the UK market, a recent data set represents a reliable sample to investigate the persistence of momentum strategies. Furthermore, it provides sufficient resources to examine whether momentum is driven by market frictions, investors' behavioural biases or both by studying the behaviour of momentum returns before and after the anomaly has been discovered. This thesis aims to investigate the issues where gaps remain and to clarify the disputes in the literature mentioned above. It also provides new methods for the investigation of some of the raised issues.

This thesis employs a unique data sample that has not been used before, at least for the momentum effect, which is the FTSE All Share constituents. The choice of the FTSE All Share stocks, which is described in more detail in the next chapter, is driven by the fact that the regulations set for the inclusion or exclusion of stocks in or out of the constituents indirectly controls for many of the micro-structural effects that have been argued to induce momentum returns. The employed data sample does not include Fledging shares and the FTSE AIM stocks which suffer from nonsynchronous trading. Given the significance of liquidity in influencing stock returns, the employed data sample is more representative than samples including illiquid and small stocks in terms of controlling for the size and liquidity effects on the overall profitability of momentum strategies. This ensures that the results are not contaminated with unrealistic profits that can not be achieved in real markets. Since the thesis attempts to resolve issues raised from previous studies, it takes great care to ensure that any observed momentum profits are not the result of well-known issues such as thin trading and the low price effect which could, otherwise, critically affect the results.

This research provides evidence of the profitability of momentum strategies for a sample period between 1983 and 2005. It also examines momentum profits from 1999 when momentum profits were first documented in the UK literature. This test explores whether the market has reacted to eliminate the observed momentum profits in the UK studies. Although, there have been several UK studies on momentum whose sample periods extend beyond the year 1999, this research is the first attempt to look at momentum returns beyond that date in a separate sub-period. The results also investigate whether arbitrageurs and other institutional investors have been able to eliminate the return continuation of the winners, losers or both.

A major claim of the limits to arbitrage theory is that institutional traders might not be able to detect the mispricing in the first place due to noise trading risk. This results in delaying the full incorporation of news into prices, which might induce autocorrelations in stock returns leading to short term continuation of stock returns. To overcome this issue, this study investigates the profitability of momentum strategies by minimising the chances of failing to detect the mispricing. This lays the ground to investigate a critical issue which is whether rational arbitrageurs are reluctant to interfere promptly due to noise trading risks. However, controlling for issues related to the failure of detecting mispricing at the right point of time is needed before testing the above issue. A sample of stocks that does not suffer from information uncertainty and illiquidity reduces the possibility of failing to detect mispricing. The thesis examines momentum profits in a sample of optioned stocks as options are found to enhance the informational efficiency of the stock prices and to increase the speed of price adjustment to news. Thus, any observed momentum profits in such a sample would hardly be attributed to the assumption that institutional investors are failing to detect mispricing or failing to learn about the value of the firms.

Furthermore, this thesis examines the robustness of momentum profits to trading costs using the traditional quoted bid-ask spread and proposes a new measure of trading costs that is more appropriate for momentum studies in that it takes into consideration the variation of the spread over the holding period rather than relying on the spread estimate during the formation period as with traditional spread cost estimates. This thesis is the first attempt to investigate the robustness of the UK momentum profits to trading costs by estimating trading cost models[8]. Moreover, since trading costs associated with the winners and losers are different – where the latter involves short

[8] Ellis and Thomas (2004) use figures from market traders and investment institutions as proxies of the trading costs on the whole portfolio but they do not estimate the costs for each of the individual stocks.

selling costs and constraints on top of other costs, such as the bid-ask spread component, broker's commission, immediacy costs, and the price impact costs – then the impact of arbitrageurs might vary with respect to the variation in the additional costs embedded. Therefore, investors might be willing to react to a certain mispricing but not to another. However, given the fact that option trading minimises short-selling costs and mitigates the constraints of the short sales, examining the momentum profits of optioned stocks provides a direct test of whether trading costs associated with the losers' side are driving momentum profits.

Also, this thesis provides new evidence on the impact of seasonality on momentum returns from testing a recent sample period. It finds supporting evidence for the recent documented April effect in the UK literature. It further finds that momentum losses due to seasonal effects have changed as a result of changes in the financial and taxation regulatory laws. This issue is addressed and compared to earlier findings.

Another contribution of this thesis is weighing the effect of firm-specific components against industry-related components in the cross-section of momentum returns. Based on evidence from previous studies that stock return volatility and the industry factor have significant influences on momentum returns, this research takes this matter a step further to examine whether the volatility effect is driven by the firm's idiosyncratic volatility or the industry's volatility. Thus, by separating the industry effect from the firm-specific effect on volatility, this research would identify the sources of the dispersion in momentum returns due to volatility.

However, since the volatility of individual stock is affected by the level of liquidity (Stoll, 1978), it is interesting to study the impact of volatility on the dispersion of momentum returns across various levels of liquidity. Furthermore, since nonsynchronous trading affects the incorporation of industry sector news into prices, it is motivating to investigate the role of the industry's volatility versus the idiosyncratic volatility in explaining the dispersion in momentum returns across different levels of liquidity.

The empirical analysis also shows that past losers becomes significantly more volatile prior to the formation date, which suggests that it is the idiosyncratic volatility that continues to influence the returns of the losers during the holding period. This finding draws implications on the difference in the return behaviour and the volatility between winners and losers prior to the formation date.

Finally, in order to assess the impact of traded options on momentum profits, the momentum profits of optioned stocks should be compared with like stocks. To construct a control sample of non-optioned stocks, this study applies a logit model that could match the return behaviour of optioned stocks. The logit model selects stocks with the highest comparability to optioned stocks with respect to the three control variables: market value, bid-ask percentage spread and volume turnover. The logit model results in a sample of stocks whose returns are nearest to the sample of optioned stocks. The model has been used in earlier studies to examine which stocks have the highest probability in getting listed on the options market. In this thesis, it is used to identify the non-optioned stocks that are most comparable to optioned stocks. The results indicate high effectiveness of the model.

1.5 Structure of the thesis

In order to investigate the issues mentioned above, the thesis is organised as follows:

Chapter 2 examines the profitability of momentum strategies for the employed sample data and sample period using two different methodologies: the non-overlapping methodology and the overlapping methodology. Chapter 2 also looks at the possibility of momentum profits being reduced or eliminated by partitioning the sample period to see the behaviour of momentum returns before and after introducing new trading systems and before and after documenting momentum profits in the UK literature. This aims to examine whether the momentum anomaly has begun to disappear as a result of advanced automated trading systems or as a result of being documented in the literature. Furthermore, tax-loss selling activities have a negative impact on momentum returns after investors repurchase back the losing stocks. This study examines whether seasonal effects driven by tax year-end selling would continue to have the same effect on momentum profits after the government had undertaken tax reforms in 1998 that aim to reduce the tax-loss selling activities. It further investigates the January and April effects on momentum returns following evidence from UK studies on the rise of an April effect and the fading of the January effect. Moreover, it studies the long-term behaviour of momentum returns to detect whether any short-term continuations are followed by long-term reversals. Finally, it checks for the possibility of market states to be affecting any negative momentum returns and adjust momentum profits for risk.

Chapter 3 addresses the impact of total volatility on the cross-section of momentum returns which is examined and compared with earlier studies. The volatility of the winner and loser portfolios is estimated using two measures: the standard deviation in stock returns and the historical High-Low-Open-Close Garman–Klass price volatility estimator. Then volatility is adjusted for industry using two techniques and the impact of idiosyncratic volatility and the adjusted volatility on the cross-section of momentum returns is estimated and discussed. Chapter 3 also studies the profitability of momentum strategies over three various liquidity level samples. Therefore, the impact of industry in explaining the cross-sectional variation in momentum returns is applied at various levels of sample liquidity. The findings suggest that the dispersion in cross-sectional losers' return is driven by the firm's idiosyncratic volatility and that the volatility of the industry plays a significant role in the cross-sectional return dispersion of winners. The results also support earlier evidence that the impact of market-wide (industry) information increases with liquidity and is less influential as the level of liquidity is decreased.

Chapter 4 investigates the persistence of momentum profits among a sample of optioned stocks to see whether stocks momentum profits could be generated after controlling for ability to sell short, availability of news and uncertainty about the value of the firm. The results are compared with four control samples of non-optioned stocks: the largest market value sample, highest turnover sample, lowest bid-ask percentage spread sample, and a control sample that is constructed using a logit model. The comparison between a sample with listed options and the control samples allow us to see whether the advantageous trading impact of options can reduce or eliminate momentum profits. The chapter also looks at the possibility of momentum profits in short run weekly based strategies. Then, the effect of the control variables on the cross-section of momentum returns is examined, and finally chapter 4 examines the robustness of momentum profits to trading costs using the quoted spread measure and the BAQET measure.

Finally, chapter 5 summarises the main findings from the empirical chapters and concludes. It also draws implications for future research in momentum studies and other research fields.

2 Chapter Two: Fading or Persisting Momentum Profits

2.1 Introduction

The momentum effect remains one of the most puzzling equity anomalies in the finance literature since it was first documented by JT (1993). Risk-based models so far have failed to explain short-run continuations in stock returns[9], and the same holds for market microstructure effects. There have been many studies that investigate the geographical scope of the momentum phenomenon and that provide international evidence (Rouwenhorst, 1998; Griffin et al. 2003), as well as UK evidence (Liu et al, 1999; Hon and Tonks, 2003; Ellis and Thomas, 2004; Galariotis et al. 2007).

While there is considerable evidence to suggest that momentum profits exist, the finance literature suggests that some anomalies disappear following their identification. For instance, the size premium (Dimson and Marsh, 1999; Horowitz et al., 2000), the value effect (Loughran, 1997) and the weekend effect (Dubios and Louvet, 1996; Schwert, 2003). Up till now, there has not been any evidence of the fading of the momentum effect at least for the UK[10]. While it may be argued that it is too early for the momentum phenomenon to weaken, the extensive attention [11] that has been given to momentum in both the academic literature and in practice may well have speeded up the process from discovery to elimination. Specifically, institutional investors/hedge funds that make up the bulk of the market have opted to exploit momentum profitability, leading to the possibility that further profit opportunities for momentum strategies are exhausted. Furthermore, changes in the trading system of the selected market, i.e. the London Stock Exchange (one example is the market system change from SEAQ to SETS)[12] can lead to faster information diffusion. This, together with modern technology and new investment vehicles should further speed up the process from discovery to elimination. Chelley-Steeley and Siganos (2006) find momentum

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[9] Chordia and Shivakumar (2002) show evidence that when alpha is allowed to vary with macroeconomic factors, the impact of firm-specific components on predicting future momentum returns weakens. However, this does not suggest that momentum represents reward for risk but it suggests that momentum profits vary with the business cycle.

[10] Henker et al. (2006) provide evidence of weak momentum profits in US market over the 2001 – 2004 period.

[11] See Menkhoff and Schmidt (2005)

[12] For more on the trading system see Galariotis and Giouvris (2007).

profits after the SETS trading system was introduced. However, their sample extends to 2001, only 2 years after momentum profits were documented by Liu et al. in 1999 for the UK, hence a longer period, that this thesis uses, is required based on the extant literature for sensible tests. Furthermore, Hon and Tonks (2003) find no evidence of momentum profits for the 1955-1976 sub-period before the momentum phenomenon was discovered and made public for any market. This supports the assumption that the momentum effect is not a permanent phenomenon, as argued by Hin and Tonks (2003), and might be subject to variation over time and, therefore, it is crucial to examine the robustness of momentum profits in the UK market to see whether momentum profits started to fade. Given the evidence on the frailty of anomalies, this chapter partitions the sample period into two sub-periods and examines whether the momentum effect persists consistently prior to and after discovery.

In addition, momentum profits are shown to vary with respect to seasonal and macro economic effects in such a way that momentum strategies would generate losses rather than profits in certain calendar months and during bad economic conditions (see for example JT, 1993; George and Hwang, 2004). In order not to mistake any fading effect for bad economic situations or seasonal effects, both issues are assessed and analysed, especially given the fact that there have been contradictory findings in the literature with respect to seasonal effects and stock returns. Also, there has been contradicting evidence on the power of macroeconomic variables in predicting momentum returns.

First, the January effect denotes that poorly performing stocks suffer from year-end high selling pressure but tend to yield abnormal returns in January, which is argued by Branch (1977) to be the result of the tax-loss selling hypothesis. On the other hand, Haug and Hirschey (2006) show that the January effect could be also attributed to the window dressing activities undertaken by institutional investors. The implications of tax-loss selling on momentum strategies are that past losers would outperform past winners and that momentum strategies, therefore, earn negative returns. JT (1993) provide evidence of negative momentum returns in January. Liu et al. (1999) provide similar evidence from the UK market while Galariotis et al. (2007) state that the January effect does not affect momentum strategies for the same market. The January effect in the UK, however, has become less apparent in favour of an April effect after the introduction of tax reforms in 1998 that aimed at reducing the tax-loss selling activity (Chen et al., 2007). If tax-loss selling is still active for individuals after the tax reform, then momentum returns would reverse in April for the UK market post–1998; alternatively, if only January calendar momentum returns were negative, then institutional window dressing activity could be said to drive the anomaly. It is therefore crucial to clarify the contradictions from earlier studies on the tax-loss induced seasonal effect and its impact on UK momentum. Given the proof of changing evidence over time, this chapter applies this approach not only to a single large sample period but to two sub-samples as well which are created by splitting the original sample period into two sub-samples at the time of introducing the new Tax Act in 1998, in order to capture the changing tax-loss selling effect on momentum returns before and after the tax reform.

Moving on, evidence on momentum performance in relation to macroeconomic effects is conflicting. For example, Chordia and Shivakumar (2002) argue that lagged macroeconomic variables can explain the performance of such strategies, but Griffin et al. (2003) disagree and show that such factors fail to explain momentum profits for a number of markets including the US and the UK. More recently, Cooper et al. (2004) show that US momentum performance is closely related to market conditions, and that momentum strategies deliver profits (losses) following good (bad) market states. Based on the findings and suggestions of Cooper et al. (2004), momentum returns are expected to be negative after the year 2000 due to global recessions and economic crises. Indeed, if momentum profits are fading, one possible explanation could be the bad market conditions in recent years. To resolve this issue, this chapter examines whether market states affect momentum profits in the UK. This has important theoretical and practical implications, especially given the current state of markets globally. More specifically, if it is true in markets other than the US that momentum strategies perform differently across different states, but in a consistent manner in each case, then, past conflicting and inconsistent momentum performance evidence may be explained, at least in part (i.e. by not differentiating between different states, past results may be erroneous). In addition, momentum investors would face less uncertainty if they can differentiate between the performance of momentum strategies under different states. Hence, this chapter also provides an out-of-sample test for this issue.

In answering the abovementioned questions, this study undertakes a test of a 23-year period using data on the FTSE All Share constituent firms for the following reasons: a) this is a major world market and, hence, is important to investors; b) it has delivered inconsistent momentum results [13], so further analysis is warranted to examine whether the contradictory evidence is due to the fact that earlier studies do not differentiate between different market states; and c) this data set has practical implications as it is a major benchmark for tracker funds and fund managers (Farrow, 2006). The FTSE All Share constituents exclude a) very small firms that suffer from thin trading and b) expensive to trade stocks that can bias results in favour of momentum profits. To increase the power of the momentum tests, non-overlapping as well as overlapping methods are employed. Furthermore, this chapter addresses a number of issues which have not been controlled for this market simultaneously. Specifically, it controls for potential non-synchronous trading of small stocks which induces positive serial correlations in stock returns (Lo and Mackinlay, 1990b). Additional evidence showing that illiquidity affects the cross-section of stock returns positively (see for example, Amihud, 2002; Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996) further justifies the representation of the data sample. The chapter also eliminates low priced stocks to control for the bid-ask bias in line with the literature (see for example JT, 2001; George and Hwang, 2004; Nagel, 2001).

The following section provides a review of the literature on momentum strategies in relevance to the aforementioned gaps in the literature that this chapter tries to address. Next, section 2.3 presents the research questions and proposed hypotheses, while section 2.4 describes data and methodology. Section 2.5 presents and discusses the results, while the final section concludes.

2.2 Literature Review

2.2.1 Overview

There has been extensive evidence on the performance of momentum strategies and the short-term positive serial correlation of stock returns. Academics have not been

[13] For example: Galariotis et al. (2007) find profits, while Hon and Tonks (2003) do not up to 1977.

able to find one common explanation that would rationalise momentum abnormal returns, the sources of which are debated extensively in the literature.

JT spot this phenomenon in their eminent paper in 1993. They find out that the recent past best performing stocks continue to outperform the recent past poorly performing stocks in the near future. In other words, past winners outperform past losers in the near future. A momentum strategy that attempt to profit from this evidence entails taking a long position in past winners and a short position in past losers and earning an abnormal return that is the expected difference in their performance over the holding period.

While most anomalies are found to disappear or to be explained by risk factors, the momentum effect persists after such considerations. In order to obtain a full grasp of the development in the literature, a review of the relevant literature is essential at this point. The first sub-section briefly reviews the historical common belief among academics and the documented anomalies that are argued to be associated to momentum profits. The next sub-section exhibits the gaps that this chapter aims to fill. At the end of the section, the sources of momentum are discussed briefly to compare with the results from this chapter and see whether this chapter could provide support to any of the proposed sources of momentum.

2.2.2 Market efficiency and return anomalies

The early empirical evidence was in support of the prevailing theory at the time as it was commonly believed among most academics that prices follow a random walk and that the market is efficient (Samuelson 1965; Fama, 1970). The efficient market theory states that all relevant information is fully and immediately reflected in a security's market price, thereby assuming that an investor will obtain an equilibrium rate of return. Since all information is rationally incorporated into stock prices with respect to the direction and the size of the price movement, the EMH implies that market participants who all have access to the same information, and who are rational, cannot make a return on a share (or other security) that is greater than a fair return for the riskiness associated with that share (or any other security).

However, the efficient market theory does not rule out the possibility of anomalies in the market that result in the generation of abnormal profits. In fact, market efficiency does not require prices to be equal to their intrinsic value at all times. Prices may divert from intrinsic values but only in random occurrences, so they eventually go back to their mean value. As such, because the deviations are themselves random, investment strategies that result in beating the market cannot be consistent phenomena (see Damodaran, 2002). Thus, a momentum strategy (or any other strategy based on past information) should not, in theory, produce any abnormal returns in an efficient market.

On the other hand, Ball and Brown (1968) show that there is a positive drift that follows earnings surprises/announcements. The striking evidence on the success of a technical analysis trading strategy was revealed by DeBondt and Thaler (1985) using contrarian investment strategies. Academics became enthusiastic about investigating other types of anomalies. The consistency of the evidence that prices do not follow a random walk challenged the EMH and the hypothesis started to lose its prominence. A variety of explanations for the return anomalies were proposed. Among these are the high transaction costs that prevent prices from being corrected. Others suggested that anomalies might be associated with the highly systematic risk of certain stocks. Recently, many academics consider human bias and the irrational behaviour of traders responsible for the occurrence of these anomalies. While specific components of stock returns could explain some of these return anomalies, they failed to justify momentum profits.

Despite the early evidence on strong market efficiency and the incorporation of future news into current prices (Schwert, 1990; Fama, 1990), several studies documented the existence of stock market anomalies. Most of these documented anomalies tend to disappear or attenuate after first documented by academics. This raises the question of whether market participants were able to implement strategies based on the anomalous behaviour of stock returns and arbitrage away profit opportunities; or whether the documented anomalies are due to selection bias, in which case there were not profit opportunities in the first place. In relation to the momentum effect, it is essential to control for microstructure effects that induce these anomalies to ensure that momentum profits are not driven by any of these anomalies. A brief review of some equity anomalies is therefore provided in the Appendix at the end of this chapter. The next subsection reviews in deep the momentum effect providing international evidence.

2.2.3 The momentum effect

JT (1993) show that, based on past stock returns, momentum strategies (relative strength strategies) which buy past winners and short past losers earn a monthly average abnormal return of 1% over the 12 months following the formation date of the momentum portfolio for the US market. Winners and losers are stocks with the highest and lowest past returns over ranking periods (3 to 12 months).

The broad literature spots more than one firm-specific component that triggers momentum in stock returns. Chan et al. (1996, 1999) show that momentum strategies based on earnings surprises (earnings momentum) also generate positive abnormal returns. They found that a substantial portion of price momentum occurs around earnings announcements. A study by George and Hwang (2004) provides evidence that the 52-week high price is a better predictor of future returns than past returns (US market). The empirical evidence identifies more than one type of momentum strategy that is found profitable over time (JT, 1993 and 2001; Chan et al., 1999), across countries (Rouwenhorst 1998; Griffin et al., 2003) and across industries (Moskowitz and Grinblatt, 1999; Lewellen, 2002; Pan et al., 2004).

The momentum effect has also been widely investigated in the UK market. Liu et al. (1999) examine the profitability of the momentum strategy for the period extending from 1977 to 1998. Using all listed stocks on the London Stock Exchange (LSE, thereafter), Liu et al. (1999) obtain momentum profits for 16 different strategies, where formation periods and holding periods vary among the combinations of 3, 6, 9 and 12 months. Their findings are in line with JT's (1993) results. Even after excluding the Alternative Investment Market (AIM)[14] stocks from their sample, momentum profits

[14] The Alternative Investment Market (AIM) is a sub-market of the London Stock Exchange. The AIM was launched in June 1995 in an attempt to offer small companies, that do not meet the requirements to be listed on other FTSE markets, the opportunity to be listed on an exchange and to help them raise

persist. Hon and Tonks (2003) investigate the profitability of the momentum strategy by extending their sample period from 1955 to 1996. Their findings suggest that the momentum effect is not a major feature of the period 1955 – 1976. A more recent data set examined by Ellis and Thomas (2004) look at the profitability of the momentum strategy during the 1990 – 2003 period. Their distinct sample consists of relatively large stocks that belong to the FTSE 350 Index. Ellis and Thomas (2004) find that their volatile sample period reflects greater momentum returns than those of earlier studies. Galariotis et al. (2007) examine the profitability of both contrarian and momentum strategies simultaneously using a data sample of all listed stocks on LSE from 1964 to 2005. They find significant evidence of momentum profits even after adjusting for survivorship and microstructure biases. However, after adjusting for Fama and French risk factors, only long-term reversals tend to disappear. Despite the extensive literature on momentum profits and their sources, the area calls for further investigation to fill the gaps that will be outlined in the following subsections.

2.2.3.1 The return characteristics of winners, losers and momentum portfolios

The momentum portfolio (winners minus losers) is found to generate positive returns up to 12 months in both the US (JT, 1993; JT 2001; Chan et al., 1996), and the UK markets (Liu et al., 1999; Hon and Tonks, 2003; Galariotis et al., 2007). Differences among studies might occur as a result of the sample period or data sets employed. For instance, Chakrabarty and Trzcinka (2006) [15] provide evidence on different results due to different databases employed. Liu et al. (1999) (for the UK) report that a truncated sample that excludes very small and illiquid stocks (AIM shares and stocks listed on USM)[16] reveals slightly different results, however the momentum effect does not disappear. Hon and Tonks (2003) find that a truncated sample period 1955 -1976 does not have significant evidence on momentum profits. Galariotis et al.

capital. The LSE website states *"that over 3000 companies from across the globe have chosen to join AIM"*. Since the AIM is an exchange regulated market segment, it relaxes most of the mandatory requirements that companies must abide by in order to be listed on the FTSE ALL Share index. http://www.londonstockexchange.com/companies-and-advisors/aim/aim/aim.htm.

[15] Chakrabarty and Trzcinka (2006) show that studies on momentum returns based on the CRSP database generate high positive returns whereas those based on the Trade and Quote (TAQ) database (database containing trades and quotes for stocks from The New York Stock Exchange) were found to generate a zero profit momentum strategy.

[16] Unlisted Securities Market (USM).

(2007) find weaker evidence of momentum profits for a sample of 6531 firms during the truncated period 1975 – 2005.

As for the winner and loser portfolios, there are some variations among the studies carried out. Using overlapping portfolios, JT (1993) find that both winners and losers generate positive returns throughout the short-term holding period; however, the winners outperform the losers. They compare the returns to the winners and losers with the value weighted index (VWI) and conclude that both winners and losers contribute about equally to momentum profits. For the UK, Liu et al. (1999) and Hon and Tonks (2003), using non-overlapping portfolios, find similar results. On the contrary, Ellis and Thomas (2004) find that the loser portfolios actually generate negative returns using overlapping portfolios. This could be due to their smaller sample (in terms of number of stocks) consisting of FTSE 350 or due to the different sample period 1990 – 2003 than that of Liu et al. (1999). It is interesting to investigate whether the negative returns to losers are attributable to the methodology used, the volatile sample period tested, or the smaller data sample employed. Another crucial aspect of winner and loser portfolios is their market value. JT (1993) and Liu et al. (1999) show that winners and losers consist mainly of smaller companies. Liu et al. (1999) also show that loser portfolios are made up of a large number of low priced stocks. Although previous evidence suggest that size and low price effects failed to explain momentum profits, these stocks have distinct return behaviour from larger stocks as the results of Ellis and Thomas (2004), who limit their data set to the FTSE 350, reveal different behaviour of losers' returns from other UK studies. Therefore, it is essential to a) look at the returns of the winners and losers using both methodologies (non-/overlapping), b) exclude very small and low priced stocks but not to limit the sample to large-cap stocks only, and c) to test an out-of-sample period.

2.2.3.2 Are momentum strategies persistent?

Based on the evidence that most anomalies tend to disappear after they are documented it is crucial to see whether the momentum strategy persists after being documented. Dimson and Marsh (1999) find that smaller companies underperform large ones for the period 1989 to 1997 in the UK. They show that the size effect produces a negative rather than positive size premium after 1989, in other words they provide evidence of the disappearance of the size anomaly. Dimson and Marsh (1999) argue that the size anomaly reversal occurred after the "*outperformance of small-cap stocks up to 1987 attracted substantial media attention*" (p. 4). There exists evidence that other anomalies disappear or reverse after being documented in the literature including value effect (Loughran, 1997), the weekend effect (Dubios and Louvet, 1996; Schwert, 2003) and the January effect that can not be exploited due to its association with the low-share price effect (Bhardwaj and Brooks, 1992).

To test whether the momentum effect delivers the same profits through changes in the market micro structure, Chelley-Steeley and Siganos (2006) test momentum profits before and after the introduction of the computerised dealer system SEAQ in October 1986. They argue that after the introduction of SEAQ, the diffusion of information among investors should be faster and hence momentum profits should be lower; however their empirical findings show that momentum profits became higher in the post-1986 period. Their findings contradict the theoretical framework of Hong and Stein (1999) that momentum profits are driven by gradual diffusion of information (positive autocorrelations) among the heterogeneous traders. They also show that after the introduction of SETS in October 1997 – a fully automated electronic auction system – "*shares trading on the SETS order-driven system demonstrate larger momentum profits than shares trading on the SEAQ quote-driven system*" (p. 5). However, their second test requires further investigation for two main reasons. First, their data sample for the SETS trading shares includes 150 stocks only. Second, if anomalies are expected to disappear after being documented in the literature – as with size effect in the UK (Dimson and Marsh 1999) – then the momentum effect, given that it was documented first by JT in 1993 for the US market and by Liu et al. in 1999 for the UK market, should tend to reduce or disappear after 1999 for the UK; while the sample period of Chelley-Steeley and Siganos (2006) extends to 2001 only, it is, therefore, motivating to look at the profitability of the momentum strategies for a longer period after 1999 period allowing more time for market participants to gradually learn about the anomaly and attempt to exploit its profits.

2.2.3.3 The January effect, the April effect and momentum profits

One very important and puzzling anomaly that is documented in the literature is the January effect. The January seasonal effect was documented by Rozeff and Kinney (1976). Roll (1983) and Reinganum (1983) suggest that the return behaviour of small stocks around the turn of the year is induced by the tax-loss selling of poorly performing stocks from the previous year. Investors tend to sell their losing stocks before the end of the tax year to realise losses. The high selling pressure on losing stocks depreciates their values by the end of December (tax-year-end in the US) before they start to gain high returns in January. Ritter (1988) shows that the incentive for the tax-loss selling is caused mainly by individual investors attempting to realise losses for tax purposes. Sias and Starks (1997) confirm the earlier evidence by showing that stocks earning abnormal January returns are mostly held by individual investors. An alternative explanation for the January effect is provided by Lakonishok et al. (1991) and Haug and Hirschey (2006) who show that part of the January return anomaly for the small-cap is attributed to the window dressing activities of portfolio managers and that any tax-motivated activity should be attributed to individual investors only. The latter argue that although the new tax-year-end for institutions became the end of October after the Tax Act of 1986, the January effect persisted after that, implying institutions' window dressing activity in addition to individual investors' tax-loss selling drive January returns. Roll (1983) and Bhardwaj and Brooks (1992) argue that the January returns are driven by high transaction costs and bid-ask biases and this is why they might not be exploitable. Since momentum strategies entail short selling losers, the low returns of such stocks in December will increase momentum profits. However, when these losing stocks bounce back in January, they should affect momentum profits negatively. JT (1993) provide evidence of negative momentum returns in January. Liu et al. (1999) and Galariotis et al. (2007) provide conflicting evidence from the UK market on the January momentum returns.

However, Draper and Paudyal (1997) show that tax-loss selling explains the high April returns but not the high January returns. It has also been shown that the January effect became less apparent than the April effect in the UK after the introduction of new tax reforms in 1998 (Chen et al., 2007). Chen et al. (2007) provide evidence that after the 1998 tax reform, the government succeeded in restricting tax-loss selling by companies but not by individuals. Draper and Paudyal (1997) show that 35% (21%) of the companies in their sample had a December (March) year-end. However, the tax-year end for individuals is the 5th of April. Since losers tend to outperform in April as well as in January, then a momentum portfolio that is short selling losers should be negatively affected at April due to the high returns of losers at that month. There are contradictory findings on seasonal effects relating to the January effect and the April effect. If tax-loss selling is still active for individuals in the UK more than for companies, and given the evidence that most companies have tax-year-end in January as well as in April (so window dressing activities would have impact in both months), then momentum portfolios should bear more losses in April than in January in the post 1998 period. It is important to look at the January and April momentum returns before and after 1998 to examine whether there is evidence that seasonal anomalies impact on momentum is changing over time.

2.2.3.4 The long-term behaviour of momentum returns

The correlation between the two phenomena – positive autocorrelations of short horizons less than a year, and long-term reversals or negative correlations over a 3-5 years period – remains disputed among academics. Behavioural studies argue that long-term reversals representing an overreaction to news follow short-term autocorrelations. Daniel et al. (1998) and Barberis et al. (1998) show, using behavioural models, that investors' biases lead to short-run momentum followed eventually by a long-term reversal. Hong and Stein (1999) also show that momentum (underreaction) is followed by a long-term reversal (overreaction), however, using a model of heterogeneous market traders interaction. JT (2001) provide empirical evidence in support of the aforementioned behavioural studies. JT (2001) show that momentum returns reverse in years 2 through 5 after portfolio formation. However, after adjusting for Fama and French risk factors, the reversal is only significant at year 4 and 5. On the contrary, George and Hwang (2004) look at the long-term behaviour of momentum returns and show that short-run momentum and long-term overreaction are not two features of the same phenomenon, i.e. short-term continuations of stock returns need not be followed by long-term reversals. Evidence from the UK reveals some contradictions to the US evidence. Liu et al. (1999) show that cumulative momentum returns remain positive by the end of the 36 months holding period; however, year 2 and 3 in isolation have negative momentum returns. Hon and Tonks (2003) show positive monthly average returns over 24 months holding period, whereas Galariotis et al. (2007) show evidence of positive cumulative momentum returns over 24 months for the sample period 1964 – 2005, momentum returns tend to reverse over the same 24 months for the sample period 1975 – 2005. None of the UK studies have used the event time methodology that is employed by JT (1993) to investigate the behaviour of the momentum portfolio in an event time. The advantage of this method using overlapping portfolios is that it increases the power of the tests and provides a month by month analysis of momentum returns over the holding and post-holding periods. A detailed look at each event month performance of the momentum strategy reveals at which month precisely momentum profits reverse – *if they do* – and whether these reversals are significant (in which case they are contrarian profits).

2.2.3.5 Market states and momentum

In addition, there has been evidence showing that momentum profits are subject to macro-economic effects. For instance, Cooper et al. (2004) show that momentum strategies are only profitable following UP markets; however, following DOWN markets, momentum strategies yield negative returns. While the evidence from Cooper et al. (2004) associate past market states (up and down markets) with momentum profits and Chordia and Shivakumar (2002) find that momentum profits could be explained by lagged macro-economic variables, Griffin et al. (2003), on the contrary, show that macro-economic factors fail to explain momentum profits for 40 international markets including the US market. Moskowitz and Grinblatt (1999) show that industry momentum strategies are stronger than individual stock momentum strategies and that once controlled for industry, momentum profits become insignificant. Although the UK market was included in Griffin et al.'s (2003) study, the market states issue has not been addressed to test its impact on momentum in the UK market. The impact of market states on momentum has been shown significant for the US market; however, to the author's knowledge, an out-of-sample test is not available up to this date.

2.2.3.6 Risk and momentum

Fama (1970) posited a joint test for market efficiency and equilibrium expected asset returns. That is, testing for market efficiency is implicitly testing for the validity of the model of expected returns. In other words, if the market is efficient, then there should be a model of the expected return that could explain abnormal returns. Any abnormal return generated is then a result of some unexpected event such as shocks to tastes or technology shocks (Fama, 1991). While market efficiency suggests that the expected return of an asset is associated to the riskiness of that asset and any random occurrence of an event, then there should exist an asset pricing model that reflects the risk factors of the asset and hence predict the expected return (Fama, 1970). Sharpe (1964) and Lintner (1965) developed the capital asset pricing model CAPM that is built on the assumption that the risk premium of an asset – expected return in excess of risk free rate – is directly proportional to the systematic risk described by the market risk premium. The CAPM however, has been shown to suffer from several pitfalls[17]. An alternative approach is developing the CAPM by adding other risk factors to it that are believed to be associated to asset returns. Fama and French (FF, hereafter) (1993) propose a multi-factor asset pricing model by appending two risk factors relating to the size and book-to-market characteristics of stock returns[18]. According to FF (1996), their three factor model (FF3F, hereafter) can capture "*many of the CAPM average-returns anomalies*" (p. 55). However, Daniel and Titman (1997) argue that size and book-to-market characteristics have explanatory power and dominate the FF size and B/M risk factors in explaining the cross-sectional patterns of average returns. They conclude that size and B/M are not risk factors in an equilibrium pricing model. So, the FF factors do not capture all of the size and value effects. The CAPM and FF3F are found unable to capture the momentum effect (See for example FF, 1996; Chan et al., 1996; JT, 2001; for the US evidence and Liu et al, 1999; Galariotis et al., 2007 for the UK evidence). While both JT (2001) and Liu et al. (1999) find that momentum profits are higher after adjusting for risk, the latter shows that the FF3F lowers momentum profits in comparison to the CAPM as opposed to JT (2001). Using a distinctive data set, this chapter provides further evidence of asset pricing models and momentum profits. Since,

[17] See Black et al. (1972) and Roll (1977) for a classical critique of the CAPM.

[18] The size and book-to-market characteristics relate to the two anomalies known as the size effect and the value effect respectively.

FF (1996) show that their model can explain contrarian profits in the long run, perhaps it is intuitive to assume that their model would have an effect on the long run momentum returns that are shown to reverse.

2.2.4 Sources of momentum

Several attempts to explain the driving forces of the momentum effect have been documented. Fama and French (1996) state that their multifactor asset pricing model could explain long run reversals but could not capture the short term autocorrelations in stock returns. JT (1995) found that due to market underreaction to earnings-related information, a momentum strategy based on past earnings surprise helps to predict future returns. A momentum strategy based on surprises surrounding earnings announcements explains 41% of momentum returns (Chan et al., 1996). On the other hand, economists in the field of behavioural finance justify momentum profits by market failure to fully incorporate news. The slow dissemination of information and investors' cognitive bias cause the market to under- or overreact. Daniel et al. (1998), Barberis et al. (1998) and Hong and Stein (1999) developed behavioural models which indicate that the underreaction and overreaction are essentially two associated components of how markets perceive news. Whereas the former suggest that short-term positive autocorrelations could be interpreted as overreaction to public news confirming private news, BSV (1998) and HS (1999) suggest that overreaction occurs after investors underreact to news. An alternative explanation is provided by Grinblatt and Han (2005) who argue that the disposition effect account for the profitability of momentum strategies[19]. Their study shows that stocks with aggregate unrealized capital gains tend to outperform stocks with aggregate unrealized capital losses. After controlling for a proxy factor of the disposition effect, Grinblatt and Han (2005) show that momentum profits disappear. Last but not least, several studies have argued that momentum profits are a product of high transaction costs (Grundi and Martin, 2001; and Lesmond et al., 2004). The reluctance of investors to exploit arbitrage opportunities

[19] Investors perceive the stocks they hold as winners or losers with respect to a reference point at which they purchased the stock. If the stock was a winner, a high selling pressure will slow the price increase and there will be a deviation between the market price and the fundamental value. This is depicted in the winners being undervalued. If the stock was a lose, investors' reluctance to sell the stock will delay its price decrease and hence it becomes overvalued over a certain period of time until the deviation between price and fundamental value reduces.

are due to high transaction costs and wide spreads that are argued to be inversely proportional to firm size. This reduces the trading frequency in small stocks – and hence the liquidity of these stocks – and accumulates unrealised gains.

Previous studies on the UK stock market also looked for possible explanations of momentum profits. Liu et al. (1999) investigate factors associated with differential average returns. They control for size, price, book-to-market ratio, and cash earnings-to-price ratio. All factors fail to fully explain momentum profits. Ellis and Thomas (2004) investigate the relationship between trading volume and momentum and conclude that stocks with higher turnover tend to have higher momentum returns. They also control for commission costs, bid-ask spread, stamp duty and short selling, however, momentum profits persist despite all the incurred costs[20]. A further attempt by Galariotis et al. (2007) examines the impact of selectivity bias, seasonality and size and shows that none of the factors could explain momentum profits even after controlling for risk.

The literature clarifies many unresolved issues regarding momentum profitability in the UK market. The purpose of this chapter is to examine whether the momentum phenomenon persists in the UK market after being documented in the literature or whether it persists after the SETS trading system has been introduced; whether seasonal effects influence the momentum profitability and if it is tax-loss selling activity that is driving such an effect; the extent duration to which momentum profits would last after portfolio formation; whether short-term positive continuations and negative correlations in stock returns are consistently related as suggested by earlier evidence from the US; and whether the predictability of momentum profits is dependable on market states. The considerable evidence on momentum profits for the UK stock market either lacks clarifications or reveals variations with respect to the proposed expectations of this chapter and, hence, demands further investigation. The identified gaps are transformed into hypotheses in the next section.

[20] Ellis and Thomas (2004) collect their estimates of trading costs from Plexis Group and market traders.

2.3 Research Questions and Hypotheses

The aim of this chapter is to examine the profitability of momentum strategies in the UK stock market using a unique dataset - the FTSE All Share constituents that is considered a major benchmark for tracker funds (Farrow, 2006). This provides useful implications for institutional traders and fund managers tracking the FTSE All share index. This study will undertake the task of testing momentum profitability using the FTSE All Share Actuaries. It should be noted that the listing characteristics of stocks that belong to the FTSE All Share index are imperative for this study since they require frequent trading and minimal market value for stocks to be enlisted. Thin trading and size are two crucial factors that might drive the results in favour of the proposed hypotheses. Moreover, it has also been shown in the literature that counter to the norm, this anomaly (momentum) is generating higher profits in recent years instead of minimising or reversing, yet the evidence comes from a small sample and up to 2001 (Ellis and Thomas, 2004).

Hypothesis 1: Momentum profits for the FTSE All Share Actuaries during the sample period 1983 – 2005 are not significantly different from zero.

Also, it has been shown above that the results for the return characteristics of winner and loser portfolios are inconsistent in the literature on the UK market. In order to clarify whether momentum profits are driven primarily by loser portfolios rather than winner portfolios, or whether both portfolios contribute equally to momentum profits, this study investigates this issue further after controlling for the low price effect. Loser portfolios are compressed with low priced stocks as shown by Liu et al. (1999).

Hypothesis 2: Losers earn negative returns during the short-term holding period of the momentum portfolio.

Hypothesis 3: There is an equal contribution to momentum profits from loser and winner portfolios.

Pricing anomalies are expected to disappear or decrease after they are identified and brought out to the public. Momentum profits were addressed first in 1993 and 1999 in the US and UK markets, respectively. Using a recent data sample this chapter examines whether market participants have been able in the last few years to exploit momentum profits. In 1997 the SETS trading system was introduced which is expected to increase flow of information and reduce underreaction to news. However, in 1999 momentum profits were first documented by Liu et al. (1999) for the UK market which indicates that investors should become aware of momentum profits in UK from 1999 onwards. These two events might have implications on the persistence of momentum profits, therefore this chapter examines the momentum profits as of the dates of the events. The sample period is partitioned into two sub-periods at 1997 (1999) to test the effect of the first (second) event.

Hypothesis 4: Momentum profits persist in the post 1997 and post 1999 periods for FTSE All Share Actuaries despite market awareness of the momentum effect.

One further documented aspect that influences stock returns is seasonal effects. Previous evidence shows that momentum returns are reversed in January due to tax-loss selling before the tax-year-end. However, empirical evidence on the UK market shows that prices are affected as well by the April effect (the compulsory tax-year-end for individuals in the UK). It is interesting to see whether momentum returns are reversed in January, April or both.

Hypothesis 5: There is an April effect that influences momentum profits in the UK due to tax-loss selling behaviour for the period 1984 – 2006.

Another gap that is identified and requires investigating is the impact of seasonal effects on momentum profits given the fact that there has been changing evidence in seasonal returns after UK tax reforms in 1998.

Hypothesis 6: The UK tax reforms in 1998 have limited the tax-loss selling activity by individuals which is evident in eliminating the April effect in the sub-period 1998–2006.

Previous research on momentum in the UK has yielded inconsistent results concerning the long term return behaviour of momentum portfolios. This chapter intends to clarify the ambiguity surrounding this matter by using the event time method with overlapping portfolios in order to see the behaviour of momentum returns in the post-holding period and to see whether momentum profits persist, disappear or reverse. Earlier findings are inconsistent. For instance, JT (2001) shows that momentum profits reverse, and they conclude that the tendency of the momentum profits to reverse is as explained by the behavioural models where underreaction is followed by an overreaction and where both these phenomena are argued to be two phases of the same phenomenon. However, George and Hwang (2004) do not find evidence to suggest that long-term reversals of stock returns follow short-term continuations.

Hypothesis 7: Momentum returns do not reverse in the post-holding period, spanning over event month 13 to 36.

To rule out the possibility that the momentum profits are not due to high systematic risk, momentum returns are adjusted to risk and then the CAPM's alpha and Fama and French alpha are estimated.

Hypothesis 8: Risk-adjusted momentum returns represented in the CAPM (or FF3F) alphas are not significantly different from zero.

According to Cooper et al. (2004), momentum strategies earn positive (negative) returns following UP (DOWN) market states. If this phenomenon applies to the UK market as well, then it would be hard to differentiate between the effect of DOWN market states in the post 1998 era and the possibility of momentum profits to disappear as a result of being identified. Given that recent bad market states period coincide with the proposed partitioned sub-period, it is essential to examine whether DOWN market states predict negative momentum returns or not.

Hypothesis 9: DOWN (UP) market states predict negative (positive) momentum returns for the UK market for the period 1983 – 2005.

2.4 Data and Methodology

2.4.1 Data

The sample employed is the FTSE All Share constituents which excludes the Fledging shares as well as the FTSE AIM stocks. The FT-SE Actuaries Fledging Index comprises all UK companies which are eligible for inclusion but are too small to be included in the FT-SE Actuaries All Share Index. Thus excluding them reduces the bias driven by very small stocks. However, as part of the FTSE All Shares constituents, the FTSE Small Cap is included which contains firms that have a comparatively smaller market value than those in FTSE 350[21]. The FTSE All Share Actuaries accounts for more than 98% of the whole UK market by market capitalisation. The large number of the eliminated stocks accounts for less than 2% of the total market capitalisation. Hence, if included, these stocks would probably gain ranking positions in the momentum portfolios (winner and loser portfolios). This, in turn, results in a small portion of the overall market value influencing the profitability of the momentum strategy from equally-weighted portfolios and therefore misrepresenting the real picture. To the knowledge of the author, there has not been any study that has examined this pivotal sample of stocks. This sutdy seeks to investigate the profitability of momentum strategies using a unique and constructive data set that is of key importance to traders.

The FTSE All Share historical constituent lists are updated annually at the end of December of each year. While the first and the last monthly constituent lists are January 1983 and December 2004 representing the reference sample, the sample holding period of monthly returns extends beyond 2004 and in some tables until 2006 and the ranking period begins as of 1982. The FTSE All Share Constituents exist on DataStream as of March 2001. Historical constituent lists prior to that date were provided by FT. Monthly stock prices are retrieved from DataStream after matching the names from the FT historical lists with the names from DataStream. Company name changes were checked

[21] The FT-SE Actuaries All Share Index consists of the FT-SE Actuaries 350 index sample and the FT-SE SmallCap. The FT-SE SmallCap consists of the UK companies within the FT-SE Actuaries All Share Index which are not large enough to be constituents of the FT-SE Actuaries 350 (FT-SE Actuaries Share Indices Steering Committee, 1995). Institute for Advanced Study, Vienna, 1997, http://www.ihs.ac.at/fin/finix/ft100descrip.html

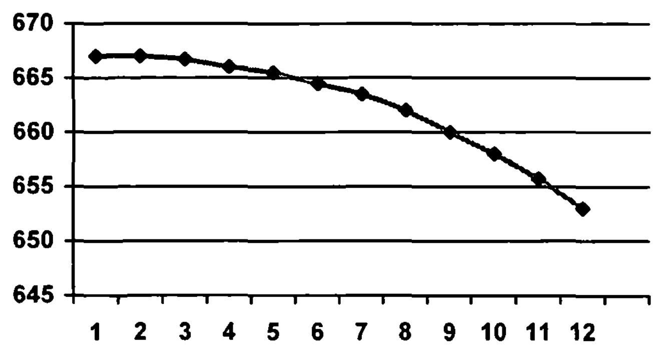
and matched from two sources. The first is the Journal of the Institute of Actuaries online Resource Centre and the second source is the Share Data Services online resource. The monthly interest rates on 1-month treasury bills are used as the risk-free rate and were retrieved from the Bank of England online database.

The data sample contains 2227 (live and dead) stocks including those entering or leaving the FTSE All Share Index list during the 23 years test period. The maximum number of constituents in any single year is 899 stocks in year 1995 and the minimum is 655 stocks in year 1992. Each stock to be included should have the sufficient price observations during the formation period. To control for the IPO effect, stocks that do not have return observations over the last 12 months before the formation date are excluded. Moreover, stocks that are not traded over 3 consecutive months during the formation period are excluded. This is to ensure that the results are not driven by problems associated to non-synchronous trading. Furthermore, low priced stocks are excluded to ensure that the results are not driven by small and illiquid stocks. Stocks with prices below 30 pence[22] at the date of portfolio formation are excluded. No restriction is placed on survival going forward, so stocks that become delisted in the holding period are removed from the study in that month.

After eliminating stocks that do not match the criteria in each formed portfolio for each month *t*, the portfolio with the maximum number of stocks is formed at October 1995 and consists of 815 stocks. The portfolio with the minimum number of stocks is formed at September 1992 and consists of 561 stocks. The average number of stocks for all portfolios is 667 and the median is 647. Therefore, the number of stocks in any portfolio is expected to decrease as the holding period extends. Figure 2.1 shows how the average number of stocks decreases across the 12 months holding period.

[22] Excluding stocks priced lower than 30 pence is roughly proportional to excluding stocks below $5 as in JT (2001), see Nagel (2001). For the years 1983, 1984 and 1985 only stocks below 20 pence are excluded since a large proportion of stocks lies beneath the 30 pence at these years.

Figure 2.1
Average number of stocks for each of the 12 months holding period following portfolio formation



2.4.2 Methodology

This chapter tests the null hypothesis of weak form stock market efficiency by examining whether looking at short-term past returns could predict future returns. If that is the case, then, the EMH will be challenged as prices will not follow a random walk or a martingale process.

2.4.2.1 Constructing the momentum portfolios

First, non-overlapping portfolios are constructed and results are compared to the existing evidence on UK stock market that used the same methodology. At month t, all stocks are ranked based on their past J monthly returns by descending order. Stocks are then assigned into deciles with the highest past performance stocks assigned to the top decile and stocks with the lowest past performance to the lowest decile. At the end of each holding period K, a new portfolio is constructed by ranking and assigning stocks within that month. The momentum strategy entails forming a zero-cost momentum portfolio by taking a long position in the top decile (winners) and a short position in the bottom decile (losers). The number of portfolios formed depends on the holding period K involved, which gives in total (integer) $\text{int}\left[\frac{264}{K}\right]$ testing periods, where 264 is the number of formation months in the sample (January 1983 – December 2004).

This study also follows JT (1993, 2001) in constructing overlapping momentum portfolios. This increases the number of testing periods and thus increases the power of the tests. At the beginning of each month t, a portfolio is constructed and held for k months. Therefore, in this manner, the winner portfolio at month t contains winning stocks in that decile as well as stocks of the past $k - 1$ winner portfolio deciles. Similarly, the loser portfolios are determined. The momentum strategy entails forming a zero-investment momentum portfolio that buys winners, sells losers and closes both positions after k months. For a given calendar month, k momentum strategies remain open at the same time. A jxk momentum strategy indicates that the formation period that is used to rank the stocks is j, whereas k is the holding period. For instance, a 12x6 strategy formed in June 1995 would consist of buying the winners in that month as well as the winners in months May, April, March, February and January of the year 1995 and selling losers using the same procedure. Notice that at month June 1995, the positions of month December 1994 are being closed and the positions of month June 1995 are being opened. This method would reflect the profitability of the jxk momentum strategy for each calendar month in the sample period. It is more realistic in that fund managers, or other traders, who are continually trading in the market update their positions on a regular basis. In this method the positions are rebalanced at the beginning of each month which makes its results more representative than the non-overlapping method.

2.4.2.2 Computation of momentum returns

To determine the momentum returns, first the continuously compounded k monthly returns for each stock are determined in the winner and loser deciles after the formation date. The return to the winner (loser) decile is the equally weighted average of the returns of all stocks in the winner (loser) decile. For the non-overlapping method, the average monthly return to a jxk momentum strategy is the average return from buying the winners and short selling the losers over the holding period k. This is determined by subtracting the mean monthly returns of the losers (bottom portfolio) from the mean monthly returns of the winners (top portfolio):

$$\overset{J\times K}{R}_{Momentum,\ t} = \sum_{t=1}^{t=k} \frac{R_{Winner,t} - R_{Loser,t}}{k} \qquad (2.1)$$

where $R_{Momentum,t}$ is the monthly average momentum profit of any month t over the holding period k; $R_{Winners,t}$ and $R_{Losers,t}$ are the mean monthly returns at month t for the corresponding winner and loser portfolios, respectively.

In order to separate the momentum effect from other factors that might generate serial correlations, the study controls for potential microstructure effects and short-run return reversals and repeats the empirical work by skipping a month between the ranking period and the holding period following JT (1993)[23] who skip a period. In a strategy that skips a month between the formation and the holding period, stocks are ranked based on their past j months returns spanning from $t-j$ to $t-1$ and the holding period for the portfolios spans over $t+1$ to $t+k$, skipping the formation month t. When a month is not skipped, the holding period spans over the t to $t+k-1$.

For the overlapping method, the winners' (losers') return is the average return of the k winner (loser) portfolios where the holding period of these portfolios start between month from $t-k+1$ and month t. The jxk strategy entails that the momentum portfolio of month t will consist of all securities that are in the winner and loser deciles of months $t-k+1$ through month t and the momentum returns are averaged over k portfolios.

$$\overset{J\times K}{R}_{Momentum,t,overlapping} = \sum_{i=t-k+1}^{i=t} \frac{R_{Winner,i,t} - R_{Loser,i,t}}{k} \qquad (2.2)$$

where i is the formation date of the portfolio, and $R_{Winner,i,t}$ and $R_{Loser,i,t}$ are the month t returns of the winner and loser portfolios, respectively, formed at month i. The time–series average of all the momentum profits represents the mean monthly profit of the momentum trading strategy $J \times K$.

[23]See also, Lo and Mackinlay (1990a) who state that "*news affect those stocks that trade more frequently first and influences the returns of thinly traded securities with a lag*" (p.188) which result in a serial covariance between stocks. JT (2001) and Cooper et al. (2004) skip a month between ranking and holding periods to minimise the effect of the bid-ask bounce.

$$\overline{R}^{j \times k}_{Momentum\_strategy} = \sum_{t=1}^{t=n} \frac{R^{jxk}_{Momentum,t,overlapping}}{n} \qquad (2.3)$$

where $\overline{R}^{J \times K}_{Momentum}$ is the average of all momentum profits and n is the number of months in the sample period.

For the event time method, the return behaviour of the momentum portfolios is examined for each event month after the date of formation. This method estimates momentum profits of the momentum portfolio for 36 months following the formation period. For each formation date, the first month's holding period returns are averaged, and the second month's holding period returns are averaged and so on. To control for the high correlation generated when cumulative returns are calculated, the Newey-West heteroskedasticity-and-autocorrelation-consistent (HAC) estimate of the variance is employed. The momentum profits from that method are referred to as raw profits. To see whether such profits are due to systematic risk, the risk-adjusted profits are also determined by adjusting raw returns to the CAPM and the Fama and French asset pricing models. The abnormal return is the intercept from the regression of the raw momentum returns on the excess returns of the market (represented by FTSE All Share) value-weighted index over the one month T-bill return for the CAPM, and additionally for the two risk factors Small minus Big (SMB) and High minus Low (HML) when applying the Fama and French (1993) model. The CAPM and FF three factor models employed are presented in the following two equations:

$$R_i = \alpha + \beta(R_m - r_f) + \varepsilon \qquad (2.4)$$

$$R_i = \alpha + \beta(R_m - r_f) + \beta_{size}(SMB) + \beta_{B/M}(HML) + \varepsilon \qquad (2.5)$$

where R_i is the raw return from a momentum strategy, r_f is the one T-bill risk-free rate of return, R_m is the return of the FTSE All Share value-weighted index, SMB is the loading factor of the return of small company stocks minus that of big company stocks, HML is the loading factor of the return of high book-to-market company stocks minus that of low book-to-market company stocks. α is the intercept from the regression, and the estimated parameters β, β_{size} and $\beta_{B/M}$, are the coefficients of the market risk, SMB and HML factors respectively and ε is a zero-mean random error term.

2.5 Results

In this section the results of testing the hypotheses put forward are presented. First, the profitability of a momentum strategy formed by non-overlapping portfolios is presented and findings are compared to earlier literature. Second, the profitability of a buy and hold strategy by forming overlapping portfolios is assessed. Then the sub-period results are assessed to examine momentum profits before and after 2 events. Fourth, an analysis of the seasonal effects on momentum profits is provided before and after changes in tax regimes. Fifth, the return behaviour of the momentum portfolios is examined in event time. Next, the study examines whether momentum profits are explained by risk. And finally, the impact of market states on momentum strategies is investigated.

2.5.1 Momentum profits using the non-overlapping methodology

In order to validate the employed data sample and to provide a reasonable comparison between the findings of this study and those of the previous studies, first non-overlapping portfolios are formed over the sample period. The results represent the monthly average return for a zero-cost portfolio that buys winners and shorts losers. Table1 shows the results from 16 different strategies, where formation periods and holding periods are the combinations of 3, 6, 9 and 12 months. The first formation date is January 1983 and the last formation date is December 2004. The formation period is denoted J and the holding period is denoted K. For every combination of *jxk*, the holding period returns for the winner (W) and loser (L) portfolios are presented as well as the return to the zero-cost winner minus loser portfolios. For example, the 6x12 strategy produces a monthly average return of 1.59% over a 12-months holding period. There are 22 non-overlapping portfolios for a strategy that holds stocks for 12 months. Therefore, the monthly average return of 1.59% is the return over each of the 12 months for all 22 non-overlapping portfolios. To have momentum profits, the winner minus loser portfolios should have statistically significant positive returns. The *t*-statistics and degree of significance are shown in parenthesis below the displayed returns.

In Panel A, the zero-cost portfolio is held straight after the formation period. The results show that the returns to all strategies are significant at 1%, 5% or 10%. In particular, the 9x6 strategy yields the highest average return of 2.44% per month compared to 1.83% and 1.56% of Liu et al. (1999) and Hon and Tonks (2003), respectively, for the same strategy. However their sample period is 1977 – 1998 and 1977 – 1996, respectively. In panel B, the strategy skips a month between the formation and holding periods and all strategies remain significant. The strategy with the highest monthly average return is the 9x3 strategy yielding 2.67%. It should be expected that the monthly average return for a short (long) term holding period is higher (lower) when a month is skipped between formation and holding periods. The reason is that return reversals caused by bid-ask bounces generate on average lower profits on the first month after formation[24]. Though the momentum profits of the first month after formation period are not very high, they are still higher than the momentum profits of later months around month 12. This is why a strategy that does not skip a month generates higher average monthly returns of 12 months holding periods. The empirical evidence in panel B shows that for every ranking period j, the monthly average return decreases monotonically as the holding period extends. For example, for a formation period of 12 months, the monthly average return decreases monotonically from 2.4%, to 2.05%, to 1.41% and to 1.05% as k increases by three months each time starting from $k=3$. Moreover, for every holding period k, the momentum profits increase monotonically as j increases (with the exception of $j=12$) in both panels.

Although the empirical findings support earlier evidence on the persistence of momentum profits in the UK, there are some noteworthy differences in the returns of the momentum portfolios. Table 2.1 reports negative returns for the loser portfolios that are significant at most times which are in contrast to Liu et al. (1999) and Hon and Tonks (2003), who show that the losers earn on average positive returns during the

[24] Later in the Event Time results section, the relatively low profits of the momentum portfolio in the first month after the formation period are shown in comparison to the profits in other months of the holding period.

holding period[25]. Using the 16 strategies as those examined in this section, Liu et al. (1999) show that losers earn on average positive returns in the holding period where Hon and Tonks (2003) find the same for 14 strategies. However, the winners in their studies gain on average higher returns than the winners in this study. These disparities in average returns of the winners and losers lead to higher momentum profits in this study than in their studies.

The incentive for these discrepancies could be caused by low priced stocks. While this study controls for the low price effect by eliminating all stocks below 30p, the other two abovementioned studies do not. Low priced stocks suffer from bid-ask bounce and are expensive to trade, and hence, might occupy ranking positions in the loser deciles without being essentially undergoing a negative trend in returns. During the holding period, low priced stocks may produce positive returns, yet lower than those of the winner portfolios, which reduces momentum profits. In particular, Liu et al. (1999) examine the impact of low priced stocks and show that the loser portfolio contains more low priced stocks than any other decile. More specifically, they find that 23.6% of the loser decile consists of stocks that belong to the lowest priced stocks quintile. According to Liu et al. (1999), the holding period returns of the loser deciles in a 6x6 strategy are 10.7% for low priced stocks and 6.6% for high priced stocks.

Another incentive for these discrepancies could be related to the impact of market states. The market states are argued to affect the profitability of the momentum strategies in such a way that negative momentum returns are generated after DOWN markets (see Cooper et al., 2004). It could be the case that losers' return was affected by market states in the post 1998 period. The post 1998 period has witnessed several macro economic and worldwide political events [26] that distressed global stock markets including the LSE. This sample period extends beyond the 1998 which earlier studies do not go beyond (Liu et al., 1999; Hon and Tonks, 2003).

In order to investigate the role of low priced stocks and the impact of market distress (in the late 90's and the beginning of the millennium) in realising high

[25] The results are compared with the (1977-1996) sub-period in Hon and Tonks (2003) study.
[26] For example, the Asian financial crisis 1998, technology-stock bubble, September 11 crisis, the war on Iraq in 2003 and the Tsunami 2004.

momentum profits, it is essential to extend the study to include more observations and be able to detect momentum returns month by month. In the next section(s) the overlapping portfolios method is applied which aims to clarify these ambiguous issues.

Table 2.1

Momentum returns using non-overlapping portfolios

At month *t*, all stocks within the FTSE All Share are ranked based on their previous *j*-month performance and held for K months. Stocks in the top decile are assigned to the Winners portfolio, and those in the lowest decile to the Losers portfolio. A zero-cost portfolio is formed by buying Winners and selling Losers. The average monthly returns of the zero-cost portfolios are presented when they are held immediately after formation date (Panel A) and a month after the formation date (Panel B). At the end of each holding period, a new portfolio is formed. The *t*-statistics are reported in parentheses. The sample period is 1983–2005.

		Panel A				Panel B			
J		K=3	K=6	K=9	K=12	K=3	K=6	K=9	K=12
3	W	0.00399 (0.785)	0.00525 (1.371)	0.00165 (0.355)	0.00381 (1.038)	0.00551 (1.319)	0.00524 (1.324)	0.00248 (0.592)	0.00340 (0.733)
3	L	-0.0093 (-1.76)^	-0.012 (-2.22)*	-0.0104 (-1.465)	-0.0101 (-1.82)^	-0.0142 (-2.48)*	-0.0142 (-2.60)*	-0.0117 (-1.516)	-0.0102 (-1.78)^
3	W - L	0.01331 (2.74)†	0.01734 (4.688)†	0.0121 (1.838)^	0.01395 (3.259)†	0.0198 (5.07)†	0.01947 (4.666)†	0.01421 (2.218)*	0.01363 (2.791)*
6	W	0.00923 (1.959)^	0.0078 (2.20)*	0.00551 (1.108)	0.0052 (1.65)	0.00863 (2.166)*	0.00743 (2.04)*	0.00539 (1.199)	0.00379 (0.95)
6	L	-0.0133 (-2.29)*	-0.0135 (-2.41)*	-0.0108 (-1.676)	-0.0107 (-1.9)^	-0.0162 (-2.64)†	-0.0156 (-2.86)†	-0.0113 (-1.67)	-0.0106 (-1.82)^
6	W – L	0.0225 (4.32)†	0.0213 (5.36)†	0.0163 (2.54)*	0.0159 (3.89)†	0.0248 (5.60)†	0.023 (5.54)†	0.0167 (2.89)†	0.0144 (3.05)†
9	W	0.00914 (1.942)^	0.00939 (2.493)*	0.0064 (1.285)	0.00568 (1.835)^	0.00951 (2.343)*	0.00904 (2.366)*	0.00624 (1.399)	0.00406 (1.09)
9	L	-0.0152 (-2.64)†	-0.015 (-2.63)*	-0.0133 (-1.85)^	-0.0113 (-1.85)^	-0.0172 (-2.79)†	-0.0155 (-2.71)†	-0.0138 (-1.82)^	-0.011 (-1.711)
9	W - L	0.02434 (4.63)†	0.02440 (5.958)†	0.01978 (2.757)†	0.01707 (3.707)†	0.02674 (5.765)†	0.02454 (5.086)†	0.02004 (3.029)†	0.01509 (2.957)†
12	W	0.01045 (2.109)*	0.00917 (2.387)*	0.00493 (0.954)	0.00332 (0.885)	0.00939 (2.15)*	0.00724 (1.779)^	0.00404 (0.794)	0.00163 (0.371)
12	L	-0.0122 (-2.18)*	-0.0125 (-2.30)*	-0.010 (-1.549)	-0.0088 (-1.635)	-0.0146 (-2.46)*	-0.0133 (-2.52)*	-0.010 (-1.542)	-0.0088 (-1.55)
12	W - L	0.02274 (4.177)†	0.02172 (5.382)†	0.01495 (2.338)*	0.01213 (2.873)†	0.02399 (4.953)†	0.02054 (4.493)†	0.01413 (2.454)*	0.01047 (2.162)*

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

2.5.2 Momentum profits using the overlapping methodology

The results in this section are of key importance, as the methodology followed here has not been applied to the FTSE All Share data sample before. Using overlapping portfolios increases the power of the tests by increasing the number of observation months and hence the number of momentum portfolios formed. Moreover, the overlapping portfolios method is more realistic in terms of financial practice. It reflects the return from forming a new momentum portfolio at the beginning of each month and liquidating another momentum portfolio that has been held for k months. Following this method, traders are allowed to have multiple positions opened concurrently. That is, at each month t and for each jxk strategy, the strategy takes a long position in k winner portfolios and a short position in k loser portfolios.

For each calendar month t in the sample period, a new zero-cost momentum portfolio is formed and another is liquated. Table 2.2 reports the returns to 16 different strategies where j and k are the combinations of 3, 6, 9 and 12 months. Winner portfolios, loser portfolios and momentum (winners – losers) portfolios are all shown for each strategy. In panel A, the results are presented for a strategy that does not skip a month between the formation period and the holding period. The most profitable strategy is the 9x3 strategy generating a 2.40% monthly average return. This is comparable to the results in table 2.1 of the same 9x3 strategy that earns 2.43%.

The findings in the previous section that the loser deciles continue to generate negative returns during the holding period are confirmed using overlapping portfolios. The striking evidence is that all loser portfolios generate negative returns and are statistically significant, whereas this is not the case for all winner portfolios. Although all winner portfolios generate positive returns, there are no significant returns over the 12 months holding periods or when the ranking period is 3 months. These findings are similar to those of Ellis and Thomas (2004)[27] and contradict the conventional view of earlier studies that show holding periods' positive returns for loser deciles (JT, 1993), Liu et al. (1999) and Hon and Tonks (2003).

For all 16 strategies but one, there is a monotonic decrease in monthly average returns as the holding period extends. This shows that momentum profits are higher at short rather than at medium horizon holding periods. However, since all strategies of 3 months holding period perform better when a month is skipped, then this implies that

[27] However Ellis and Thomas (2004) do not report the t-statistics for the winner and loser portfolios

there exist some short-term reversals after the portfolio formation date in support of the evidence from Antoniou et al. (2006).

Table 2.2

Momentum returns using overlapping portfolios

At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous *j*-month performance and held for K months. Stocks in the top decile are assigned to the Winners portfolio, and those in the lowest decile to the Losers portfolio. A zero-cost portfolio is formed by buying Winners and selling Losers. The average monthly returns of the zero-cost portfolios are presented when they are held immediately after formation date (Panel A) and a month after the formation date (Panel B). The *t*-statistics are reported in parentheses. Obs is the number of observation months for each strategy. The sample period is 1983–2005.

		Panel A				Panel B			
J		K=3	K=6	K=9	K=12	K=3	K=6	K=9	K=12
3	W	0.0043	0.0040	0.0034	0.0035	0.0047	0.0042	0.0034	0.0030
		(1.17)	(1.10)	(0.95)	(0.96)	(1.27)	(1.17)	(0.94)	(0.83)
3	L	-0.0116	-0.0133	-0.0118	-0.0108	-0.0145	-0.0135	-0.012	-0.0107
		(-2.36)*	(-2.75)†	(-2.50)*	(-2.31)*	(-2.94)†	(-2.82)†	(-2.55)*	(-2.31)*
3	W – L	0.0160	0.0173	0.0153	0.0144	0.0192	0.0177	0.0154	0.0138
		(4.62)†	(5.91)†	(6.06)†	(6.22)†	(5.81)†	(6.37)†	(6.42)†	(6.19)†
6	W	0.0084	0.0073	0.0069	0.0057	0.0078	0.007	0.0063	0.0046
		(2.26)*	(1.97)*	(1.87)^	(1.54)	(2.09)*	(1.91)^	(1.71)^	(1.24)
6	L	-0.0146	-0.015	-0.0133	-0.0114	-0.016	-0.015	-0.0129	-0.0107
		(-2.85)†	(-2.99)†	(-2.70)†	(-2.35)*	(-3.26)†	(-3.03)†	(-2.63)†	(-2.23)*
6	W – L	0.0231	0.0223	0.0202	0.0171	0.0240	0.0220	0.0190	0.015
		(6.12)†	(6.60)†	(6.57)†	(5.91)†	(6.65)†	(6.84)†	(6.41)†	(5.45)†
9	W	0.0092	0.0084	0.0068	0.0050	0.0084	0.0078	0.0058	0.0038
		(2.47)*	(2.27)*	(1.84)^	(1.36)	(2.24)*	(2.13)*	(1.57)	(1.02)
9	L	-0.0148	-0.0152	-0.0134	-0.0111	-0.0169	-0.0152	-0.0127	-0.0104
		(-2.88)†	(-3.01)†	(-2.67)†	(-2.24)*	(-3.29)†	(-3.02)†	(-2.56)*	(-2.12)*
9	W – L	0.0240	0.0236	0.0202	0.0162	0.0253	0.0230	0.0185	0.0142
		(6.17)†	(6.54)†	(5.88)†	(4.98)†	(6.63)†	(6.52)†	(5.48)†	(4.47)†
12	W	0.0101	0.0078	0.0054	0.0037	0.0092	0.0065	0.0042	0.0025
		(2.62)†	(2.04)*	(1.42)	(0.94)	(2.38)*	(1.70)^	(1.08)	(0.64)
12	L	-0.0137	-0.0137	-0.0117	-0.0095	-0.0153	-0.0135	-0.0110	-0.009
		(-2.69)†	(-2.71)†	(-2.34)*	(-1.93)^	(-3.01)†	(-2.69)†	(-2.22)*	(-1.84)^
12	W – L	0.0238	0.0215	0.0172	0.0133	0.0246	0.0200	0.0152	0.0115
		(5.91)†	(5.61)†	(4.70)†	(3.86)†	(6.15)†	(5.30)†	(4.23)†	(3.43)†
	Obs.	262	259	256	253	262	259	256	253

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

It is also notable that the magnitude of the losers' return greatly exceeds that of the winners'. This intriguing finding suggests that the underperformance of the loser portfolios contributes more to momentum profits than the winners portfolios. This characteristic is inconsistent with JT (1993) suggestion that both winners and losers "contribute about equally" to the momentum profits. In panel B, results are presented when a month is skipped and the results are similar to those in panel A, except that a strategy that skips a month earns more than a strategy that does not skip when $k = 3$; however, as k tends to increase this phenomenon subsides.

2.5.3 Partitioning the sample period

In this sub-section, two sample period partitions are applied, whereas each time the sample period is split into two sub-periods. The first sub-period is 1983–1996 and the second sub-period is 1997–2005. The purpose of splitting the sample period is to investigate whether momentum returns after 1996 have been affected by the introduction of the fully automated electronic auction system in LSE. The results would also reveal whether momentum profits during the 1997–2005 sub-period are so high, which drives the momentum profits of the whole sample period to be larger than earlier studies.

The second partition splits the sample into the 1983–1999 sub-period and the 2000–2005 sub-period. Splitting the sample after 1999 provides a test of whether market participants became aware of the momentum profits phenomenon and were are able to exploit these profits. Since the profitability of the momentum strategy has been widely documented in the literature, and the positive serial correlations have been noticed in stock returns over short to medium-term horizons, it is expected that market participants and especially institutional investors would become aware of these profits and should be taking action of any arbitrage opportunity. If momentum profits, however, do not disappear in the latter sub-period, then it is either high transaction costs or market underreaction that produces these abnormal returns.

Table 2.3 panel 'A' exhibits the results for two sub-periods 1983 – 1996 and post 1996, while panel B exhibits the results for the second partition. A momentum strategy that is ranked on the past 6 months is considered representative for other strategies based on past 3, 9 or 12 months and thus would suffice to report only the returns to the *6xk* strategies. The winner and loser portfolios are presented as well as the return to the zero-cost momentum portfolios. Table 2.3 also presents the number of months within each sub-period and show that none of the strategies in both sub-periods is biased by small number of observation months.

2.5.3.1 Testing the two sub-periods 1983 – 1996 and 1997 – 2005 separately

First, the results of the first partition are discussed. The notable findings, however, arise from the returns to the winner and loser portfolios within both sub-periods. For example, the return to the winner portfolio of the 6x3 strategy in the first sub-period (1.2%) is 20 times larger than that in the second sub-period (0.06%); whereas the return to the losers in the first sub-period (-1.1%) is less than half that of the second sub-period (-2.6%). It is evident that the monthly average returns to all winner portfolios within the 1983–1996 are statistically significant at 1% or 5% levels. The returns to the winners are also slightly larger (in magnitude) than those of the losers for all reported strategies. The monthly average returns for the loser portfolios are negative and are only significant up to the 6 months holding period. These figures tend to change in the 1997–2005 sub-period where the loser portfolios are all significantly negative; whereas the positive returns from the winner portfolios fade and become negative, yet these negative returns are not significant. On the other hand, the momentum strategy is profitable and statistically significant for all strategies and for both sub-periods.

The results from these two sub-periods clarify much of the ambiguity of the proposed questions. Firstly, the negative returns of the loser portfolios are present at both sub-periods; however they are higher during the second sub-period. Contrary to the findings of Liu et al. (1999) and Hon and Tonks (2003) who find positive returns for losers over short to medium-horizons, this study shows the opposite. While their samples do not go beyond 1998, findings here suggest that the negative returns of the loser portfolios are not driven by post-1996 results, as they are also negative and significant in first sub-period over short-term horizons. This means that the obtained negative returns for the loser portfolios over short to medium-term holding period is a feature of the FTSE All Share Constituents. Secondly, the significantly positive returns to the winner portfolios during the first sub-period become negative in second the sub-period. Thirdly, momentum profits during the 1983–1996 are greater than those in earlier studies. In other words, momentum profits in the second sub-period are not driving the large momentum profits of the whole sample period. Last but not least, the results shown from the two sub-periods confirm the earlier suggestion that the major contribution for momentum profits arise from the losers' side. Consider the 6x6 strategy, in the first sub-period, the winners' return exceeds the return on the value-weighted index (VWI) by 0.22%, whereas the losers underperform the index by 1.96%. In the second sub-period, the results are even more persuading where the winners underperform the index by 0.29% and the losers underperform the index by 2.2%.

To better grasp the differences between both sub-periods, the returns to the 6x6 strategy are depicted in a chart for each calendar month within both samples. Figures 2.2 and 2.3 depict momentum returns over both sub-periods, respectively. Negative momentum returns appear more frequently in the second sub-period which experienced several short-term bear markets. As it is shown in Figure 2.3, momentum returns are negative after the July 1998 (Asian financial crisis), January – March 1999 (UK economy recession), January 2000 (technology bubble), September 2001 (Sep 11 attacks) and March 2003 (war on Iraq) events. Moreover, the monthly average VWI return of the FTSE All Share in the second sub-period is -0.45% compared to 1% in the first sub-period. Given all this, the state of market in the second sub-period could explain the lower returns to winners and losers. However, this should not necessarily affect the overall profitability of the momentum strategy. Negative momentum returns might appear due to bad events, but shortly afterwards they bounce back. For instance, the monthly average return for a 6x6 strategy in the second sub-period is considerably high 2.20%. To conclude this sub-section, momentum profits are not found to disappear for the sub-period 1997–2005. However, the returns of the winners and losers are shown to fall in times of bear markets. The inference from this empirical evidence is that momentum strategies are still profitable in times of bad market states and for horizons that exceed 6 months.

Table 2.3

Momentum returns using overlapping portfolios for sub-periods

This table presents the momentum returns within two sub-periods. At each month within the sample period, all stocks within the FTSE All Share Actuaries are ranked based on their past 6 months returns and held for *k* months. Stocks in the top decile are assigned to the Winners portfolio, and those in the lowest decile to the Losers portfolio. A zero-cost portfolio is formed by buying Winners and selling Losers. The average monthly returns of the zero-cost portfolios are held when a month is skipped after the formation date. At the end of each holding period, a new portfolio is formed. In Panel A, the last portfolio in the first sub-period is formed in December 1996 and the first portfolio in the second sub-period is formed in January 1997. In Panel B, the last portfolio in the first sub-period is formed in December 1999 and the first portfolio in the second sub-period is formed in January 2000.The *t*-statistics are reported in parentheses. Obs is the number of observation months for each strategy. VWI is the average return on the FTSE All Share value-weighted index for the two sub-periods. The sample period is 1983–2005.

Panel A

		1983 – 1996				1997 – 2005			
J		K=3	K=6	K=9	K=12	K=3	K=6	K=9	K=12
6	W	0.012 (2.72)†	0.0118 (2.67)†	0.0113 (2.52)*	0.0099 (2.19)*	0.0006 (0.089)	-0.0011 (-0.18)	-0.002 (-0.32)	-0.004 (-0.64)
6	L	-0.011 (-2.01)*	-0.01 (-1.82)^	-0.0086 (-1.56)	-0.0068 (-1.23)	-0.026 (-2.59)*	-0.0238 (-2.45)*	-0.02 (-2.15)*	-0.017 (-1.92)^
6	W – L	0.0231 (6.36)†	0.0219 (7.63)†	0.0199 (7.51)†	0.0167 (6.68)†	0.0267 (3.14)†	0.0226 (3.1)†	0.018 (2.7)†	0.013 (2.11)*
	Obs.	166	163	160	157	96	96	96	96
	VWI	0.0096 (2.49)*				0.0018 (0.39)			

Panel B

		1983 – 1999				2000 – 2005			
J		K=3	K=6	K=9	K=12	K=3	K=6	K=9	K=12
6	W	0.0118 (3.01)†	0.0117 (2.97)†	0.0113 (2.84)†	0.0099 (2.49)†	-0.0056 (-0.59)	-0.0086 (-1.00)	-0.0101 (-1.19)	-0.0125 (-1.45)
6	L	-0.0111 (-2.30)*	-0.0103 (-2.13)*	-0.0087 (-1.81)^	-0.0070 (-1.46)	-0.0351 (-2.33)*	-0.0312 (-2.17)*	-0.0265 (-1.94)^	-0.0228 (-1.73)^
6	W – L	0.0230 (8.19)†	0.0221 (8.32)†	0.0200 (8.05)†	0.0169 (7.27)†	0.0294 (2.25)*	0.0225 (2.05)*	0.0164 (1.65)	0.0102 (1.10)
	Obs.	202	199	196	193	60	60	60	60
	VWI	0.0102 (3.00)†				-0.0045 (-0.78)			

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

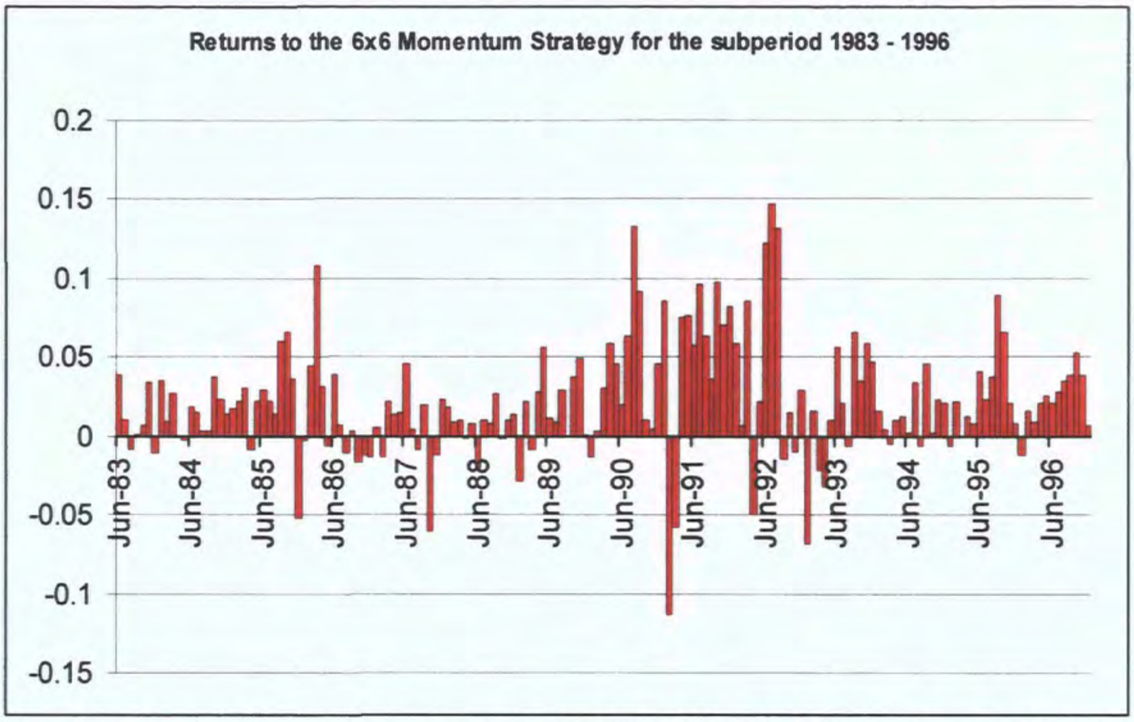


Figure 2.2. The monthly momentum returns for the 1983 – 1996 sub-period based on past 6 months returns and with a holding period of 6 months, using overlapping portfolios.

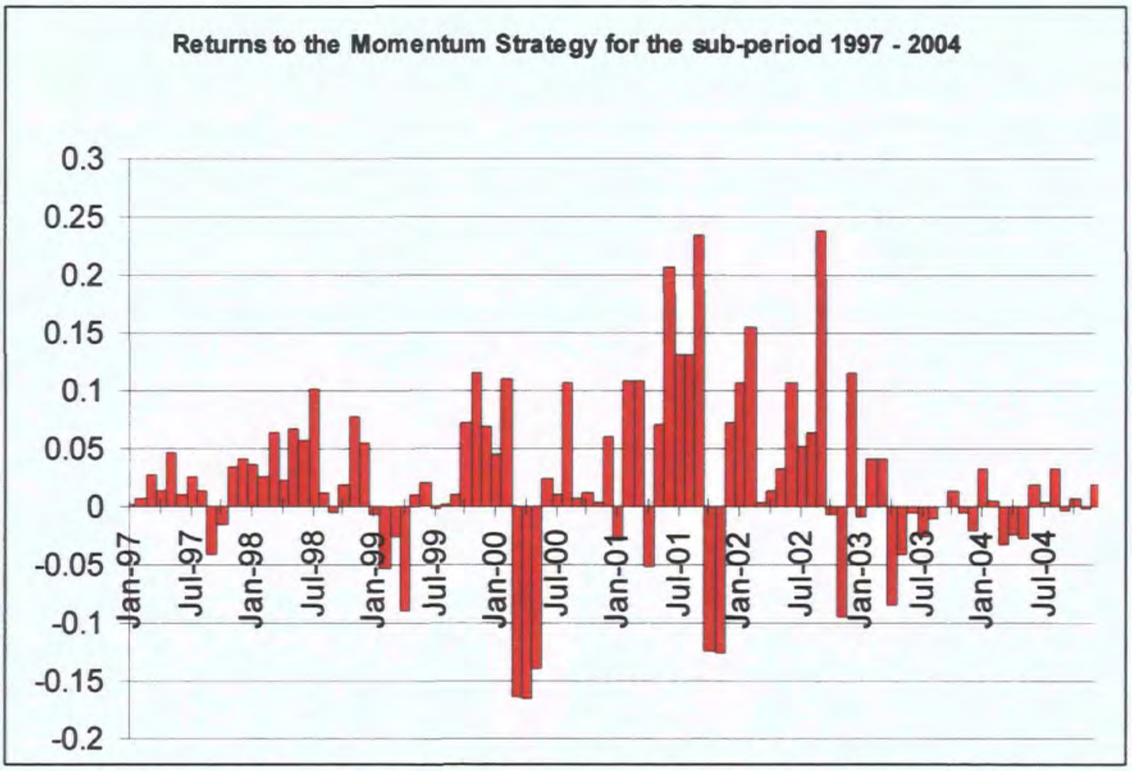


Figure 2.3. The monthly momentum returns for the post 1997 sub-period based on past 6 months returns and with a holding period of 6 months, using overlapping portfolios.

2.5.3.2 Testing the two sub-periods 1983 – 1999 and 2000 – 2005 separately

In this subsection, the results from the second partition are discussed to examine whether momentum profits disappeared or reduced after being documented for the UK market in 1999. Table 2.3, panel B exhibits the results for this subsection. The returns to the winners are larger (in magnitude) than the returns to losers during 1983–1999. This tends to change in sub-period 2000–2005, as in the previous subsection, where the return to losers becomes larger (in absolute terms) than that of the winners. However, the impact of bad market states on lowering the winners' and losers' returns is more prevalent in the sub-period 2000–2005. For example, in the 6x6 strategy, the monthly returns to winners (losers) decline from 1.17% to –0.86% (–1.03% to –3.12%) from the first sub-period to the second sub-period, respectively.

The remarkable finding in this sub-section is that momentum profits start to fade away beyond a 6 months holding period for the 2000–2005 sample. Momentum profits are shown to be significant for the 6x3 and 6x6 strategies but not for the 6x9 and 6x12 strategies. The momentum profit for the 6x9 strategy is 1.64% with a t-statistic of 1.65 and that of the 6x12 is 1.02% with a t-statistic of 1.10%. One possible explanation could be the impact of the bad market conditions during that period on momentum profits which suggests that momentum strategies earn negative returns during distressed market periods. However, since momentum profits are significantly positive up to a holding period of 6 months, then the assumption of the impact of bad market conditions on momentum profits is assumed to affect only momentum strategies of holding horizons beyond 6 months. To investigate this matter further, this chapter examines the impact of market states on momentum profits in a later section.

On the other hand, the fading momentum profits beyond a 6 months holding period could be due to market gradual awareness of momentum profits throughout the holding period and the attempt of market participants to eliminate arbitrage opportunities during the momentum cycle. This assumption that market participants become *gradually aware* of arbitrage opportunities implies that they are capable of eliminating momentum profits at a delayed time. In other words, momentum profits could be realised at first over a short period before they are eliminated by market participants. These empirical findings could provide further evidence to the suggestion made by Hong and Stein (1999) regarding the gradual diffusion of information among heterogeneous investors that results in short-term return continuations. Hong and Stein (1999) also argue that a momentum builds up and eventually bursts after market traders attempt to join the cycle at a delayed time. Therefore, it should be expected that momentum profits fade away at longer horizons. Moreover, since momentum strategies based on past 9 months and past 12 months indicate that winners and losers are being observed further by market participants, then it should be more likely that their momentum cycle is near to end not long after formation date. Based on the gradual awareness assumption, therefore, strategies with longer ranking periods should generate, contrary to the norm, lower and insignificant momentum profits.

Table 2.4 reports the momentum strategies of the 2000–2005 sub-period for j=3, 9 and 12 and k=3, 6, 9 and 12 months. The results are very intriguing. First, for a strategy based on past 3 months' performance, significant momentum profits decline monotonically as the holding period extends. These momentum profits are not significant at the 12 months holding period. Second, for a strategy based on past 9 months' performance, all momentum profits are insignificant yet positive. Furthermore, it is clear that momentum profits are declining as the holding period extends. Last, for momentum strategies based on past 12 months' performance, the momentum returns are lower than other strategies, and there are negative returns over the 12-months holding period. Thus the larger the ranking period or the holding period the lower the momentum returns, and vice versa. The 3x3 strategy, therefore, has the highest monthly average momentum return 2.45% and the 12x12 strategy earn the lowest monthly average momentum return –0.21%. These findings are the consequence of the returns to winner and loser portfolios. While winners' returns decline monotonically as j or k extends, losers' returns increase monotonically when either j or k extends. This is true for all 12 strategies in table 2.4. The profitability of momentum strategies over shorter ranking and holding periods but not long horizons suggests that the news dissemination is faster than in the earlier sub-period. Table 2.3 panel B shows that for the 1983–1999 sub-period, the winners earn significant positive returns and momentum profits are significant even at the 12 months holding period. Momentum profits during the 1983–1999 sub–period are not necessarily higher than the latter period, but what is evident is that the momentum cycle is longer during the 1983–1999 sub-period as shown by the significance of the 12 months holding period strategy. The findings for the 2000–2005 sub-period support the notion of gradual awareness among market participants about momentum profits.

These findings contradict those of Chelley-Steeley and Siganos (2006) who argue that momentum profits over time does not support the theory of gradual diffusion of information. Using the duration of momentum strategies as well as a more recent sample period, this study shows that market participants may be gradually learning. This could be an early sign of market anticipation to momentum profits. However, given the limited testing period available after year 2000, a further investigation requires a larger testing window. However, it is still premature to fully conclude from these results that the momentum effect has actually started to gradually disappear by generating non-significant returns beyond 6 months holding periods.

Table 2.4

Momentum returns for the post 2000 sub-period

This table presents the momentum returns for the 2000–2005 sub-period. Momentum portfolios are formed as in table 2.2. The monthly average returns of the zero-cost portfolios are presented when a month is skipped after the formation date. The *t*-statistics are reported in parentheses. Obs is the number of observation months for each strategy. VWI is the average return on the FTSE All Share value-weighted index for the two sub-periods. The sample period is 2000–2005.

		2000 – 2005			
J		K=3	K=6	K=9	K=12
3	W	-0.0079 (-0.81)	-0.0093 (-1.05)	-0.0120 (-1.42)	-0.0127 (-1.47)
3	L	-0.0324 (-2.17)*	-0.0316 (-2.29)*	-0.0274 (-2.07)*	-0.0249 (-1.96)^
3	W – L	**0.0245 (1.97)^**	**0.0223 (2.24)***	**0.0154 (1.86)^**	**0.0122 (1.61)**
9	W	-0.0095 (-1.01)	-0.0099 (-1.15)	-0.0129 (-1.50)	-0.0154 (-1.77)^
9	L	-0.0310 (-2.03)*	-0.0262 (-1.82)^	-0.0227 (-1.64)	-0.0198 (-1.51)
9	W – L	**0.0215 (1.60)**	**0.0163 (1.39)**	**0.0097 (0.88)**	**0.0043 (0.43)**
12	W	-0.0102 (-1.0)	-0.0141 (-1.45)	-0.0170 (-1.75)^	-0.0188 (-1.88)^
12	L	-0.0244 (-1.62)	-0.0221 (-1.54)	-0.0189 (-1.39)	-0.0166 (-1.28)
12	W – L	**0.0142 (1.02)**	**0.0080 (0.62)**	**0.0019 (0.16)**	**-0.0021 (-0.20)**
	Obs.	60	60	60	60

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

2.5.4 Calendar returns and seasonal effects

In this subsection, the impact of seasonal effects on momentum profits is examined to see whether the latter are influenced by any tax-loss selling activities or window dressing activities. The evidence from the US studies shows that momentum profits are reversed in January due to the January effect first documented by Rozeff and Kinney (1976). The common belief in the literature on the US market suggests that the January effect is a small-cap phenomenon (see Reinganum, 1983; and Roll, 1983). However, this chapter excludes the very small stocks from the study and, hence, this exclusion should in turn minimise the small firm effect at the turn of the year. The negative January momentum returns are attributed to tax-motivated selling by individual investors at the turn of the year (see for example Ritter, 1988) and to window dressing trading activity by institutional investors who tend to sell their losers before the end of the year to improve perceived performance (Lakonishok et al., 1991). JT (1993) and George and Hwang (2004) provide evidence of negative momentum returns in the January calendar months of their sample periods.

For the UK market, the tax-year-end is April 5th for individuals, and the 31st of March or 1st of January for more than half of the companies (see Draper and Paudyal, 1997). Draper and Paudyal (1997) show that high April stock returns but not high January stock returns are explained by tax-loss selling. Testing a more recent sample, Chen et al. (2007) show that the negative relationship between a stock's past performance and its April return continues to exist after new rules have been implemented to limit tax-loss selling by individuals. They find positive relationship between past returns and January returns and suggest that changes to the tax rules in 1998 were successful in reducing tax-loss selling by the company sector only. If seasonal anomalies have impact on the returns to winner and loser portfolios in the UK, then tax-motivated selling, which is argued to affect stock returns seasonally, should affect momentum returns. Since the tax-year-end is the 5th of April for individuals and given the evidence on persisting tax-loss selling activities by individuals, seasonal effects on momentum returns are expected to be observed in April[28]. On the other hand, negative momentum returns on January would be observed if there are window dressing

[28] According to Chen et al (2007) individuals owned 28% of ordinary shares listed on the UK market in 1981 and this figure fell to 14% in 2002.

activities by institutional investors. It is expected to observe a negative relationship between a stock's prior to April returns and its April returns if it was underperforming the market. Since the loser portfolios are the past lowest underperforming stocks in the market then the loser portfolios' April returns should be positive, which reduces the April momentum returns.

Table 2.5 presents momentum returns by calendar month, together with the proportion of months in which momentum returns are positive. As can be seen, momentum strategies are profitable with an average return of 2.22% per month (at the 1% level of significance). April is associated with negative momentum returns, consistent with expectations that individuals are engaging in tax-loss selling. Furthermore, April is the only calendar month with an average negative return, however, the negative return is statistically insignificant. Note however that this insignificance may be due to the fact that the study does not differentiate between the two tax-regimes. Despite the insignificant returns in April, the profitability of momentum excluding April increases to 2.30% (1% level of significance). The momentum strategy appears to be more profitable at some calendar months than at others. Table 2.5 also displays the proportion of instances where positive returns are experienced for each calendar month. Not surprisingly, the figure is lowest for April and January (56% and 47%, respectively), i.e. immediately following the period when individuals and the majority of firms have their tax-year ends and when they engage in readjusting their portfolios. The proportion of positive returns is highest for February, June and July (87%, 87% and 91% respectively). There are 5 insignificant positive momentum returns in calendar months January, March, May, October and November. The reason for low momentum profits in January and March can be attributed to institutional tax-loss selling or window dressing[29].

The January and April figures are consistent with tax-loss selling and also with window dressing. Whether the incentive is window dressing or tax-loss selling, the selling pressure on the losing stocks depresses their prices and increases momentum profits during December (and February), but when prices bounce back in January (and

[29] In the case of window dressing, institutional investors sell embarrassing losers and purchase good winners before reporting on their portfolios. This has the effect of depressing the prices of losers and increasing the prices of winners, leading to higher returns for momentum portfolios which reverses afterwards.

April), momentum profits seem to disappear. Table 2.5 reports also the returns to the winner and loser portfolios at each calendar month to see whether any seasonal effect depicted in the negative April returns and low January returns are arising from the winners' or the losers' side. The window dressing activity should influence the returns of the winners as well as the losers, in that institutional investors sell their losing stocks (further depressing losers' prices) and acquire winning stocks increasing their prices. The winners' returns are significantly positive in December, January and February only. This finding indicates that institutional investors are involved in window dressing activities with respect to acquiring winning stocks. The April return to the winner portfolio is 1.08% which is highest after these 3 months and is statistically significant (t-value 0.90). The January losers' return is the only significantly positive return for the loser calendar months. Since the January is associated with institutional investors only, the reported 2.44% (10% level of significance) could be attributed to either window dressing or tax loss selling by institutional investors.

Losers also experience positive returns in April, 1.79%, but is statistically insignificant. However, the losers' positive April return could be associated with either individual or institutional investors. Prior to the positive returns in January and April, the losers experience negative returns. This could be due to companies and individuals offloading losers and holding on to winners, anticipating the March year end for a large number of institutional investors and 5th of April year end for individuals.

As can be seen by the *F*-statistics, consistent with all the above, momentum appears to be more profitable when testing for all months and when excluding the earlier insignificant January month (*F*-statistic: 1.66 and 1.69, respectively) compared to an insignificant *F*-statistic of 1.05 when excluding April. In other words, when April returns are excluded, the *F*-statistic does not suggest any significant difference among the returns of the other 11 calendar months (May – March). However, when April is included, the *F*-statistic indicates that there is a significant difference among the returns of 12 calendar months. Including or excluding January does not affect the results. This last finding implies that the differences can be driven by either institutional trades or by individual investors' year-end activities as suggested by Chen et al. (2007).

Table 2.5

Holding period returns by calendar months

This table presents momentum, winner and loser returns for each calendar month and the proportion of months with positive momentum returns. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their past 6 month returns and held for 6 months. Stocks in the top decile are assigned to the Winner portfolio, and those in the lowest decile to the Loser portfolio. A zero-cost portfolio is formed by buying Winners and Selling Losers. For each calendar month, we report the proportion of positive returns for that month. We also report the average monthly returns of the zero-cost portfolios in each calendar month. At the end of each holding period, a new portfolio is formed. *F-statistics* test the null hypothesis that the difference in returns of momentum portfolios in calendar months is zero. F_{All}, F_{Apr} and F_{Jan} test the null hypothesis that the momentum returns are equal among all calendar months, May through March and February through December, respectively. The *F-critical* values are reported in parentheses under each test. The *t*-statistics are reported in parentheses. The sample period is 1984–2006.

	Momentum returns by calendar months	Proportion of positive momentum returns	Winner returns by calendar months	Loser returns by calendar months
Jan	1.29 (1.49)	0.47	3.73 (4.00)†	2.44 (1.84)^
Feb	2.46 (2.00)^	0.87	2.63 (2.80)*	0.17 (0.10)
Mar	1.33 (0.98)	0.60	-0.29 (-0.22)	-1.62 (-1.27)
Apr	-0.71 (-0.62)	0.56	1.08 (0.90)	1.79 (1.33)
May	1.18 (1.18)	0.69	0.37 (0.31)	-0.81 (-0.71)
Jun	3.94 (3.83)†	0.87	-0.05 (-0.05)	-3.99 (-2.33)*
Jul	3.51 (3.84)†	0.91	-0.28 (-0.24)	-3.79 (-2.25)*
Aug	3.19 (3.27)†	0.65	1.12 (0.75)	-2.06 (-1.08)
Sep	4.36 (2.96)†	0.73	-1.34 (-1.06)	-5.70 (-2.33)*
Oct	1.73 (1.69)	0.73	0.01 (0.01)	-1.72 (-0.94)
Nov	1.87 (1.61)	0.69	0.61 (0.54)	-1.26 (-0.79)
Dec	2.54 (3.15)†	0.78	2.24 (3.09)†	-0.30 (-0.29)
All months	2.22 (5.62)†	0.72	0.82 (2.21)*	-1.40 (-2.46)*
May-Mar	2.30 (5.94)†	0.73	0.92 (2.43)*	-1.38 (-2.33)*
F-*statistic*$_{All}$	1.66^ (F-*critical* 1.59 at 10%)		1.41 (F-*critical* 1.59 at 10%)	2.12* (F-*critical* 1.82 at 5%)
F-*statistic*$_{Apr}$	1.05 (F-*critical* 1.62 at 10%)		1.54 (F-*critical* 1.62 at 10%)	1.85^ (F-*critical* 1.62 at 10%)
F-*statistic*$_{Jan}$	1.69^ (F-*critical* 1.62 at 10%)		0.88 (F-*critical* 1.62 at 10%)	1.66^ (F-*critical* 1.62 at 10%)

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

For a full comprehension of why these results differ from those of Liu et al. (1999) who find a January effect on momentum returns, this chapter takes into consideration the changing evidence over time to be responsible for the differences. Since it was shown that tax-loss selling tended to disappear for companies but not for individuals after the introduction of the 1998 Tax Act, then only individuals' tax-loss selling taking place on April should affect momentum profits. Therefore, the sample period is partitioned at the end of 1998 to examine the impacts of the new Tax Act on momentum returns. It is expected to observe negative April momentum returns as a result of the post-1998 individuals' tax-loss selling. It is also expected that the low January momentum returns increase in the post-1998 period as a result of the new Tax Act set by the government that limited that tax-loss selling activities by institutions as argued by Chen et al. (2007).

Next, the chapter presents the results relevant to the calendar effects but following sample partitioning. The purpose of this partitioning is to capture the impact of the individual's tax-loss selling on seasonal momentum returns after the introduction of the new Tax Act in 1998. This suggestion is based on the evidence from earlier UK studies of the disappearance of the January effect (Chen et al., 2007) and on evidence that tax-loss selling explains the high April returns but not the high January returns (Draper and Paudyal, 1997). Table 2.6 reports the momentum profits for each calendar month in the two sub-periods 1983 – 1998 and 1999 – 2006, allowing for a small period of adjustment for the effect of the new regulations to sink in and to affect the strategies. Results show that before the 1998 Act, momentum strategies experience positive returns in all 12 months, 9 of which are statistically significant from March to November. The highest return is 3.69% for July (*t*-statistic 3.39), closely followed by June with a return of 3.36% (*t*-statistic 4.13). In addition, although April returns are significant, they are, at the same time, the smallest among all the significant months. There is no turn of the year effect, since returns from December to February are insignificant. Neither April nor January momentum returns are negative during the first sub-period. This implicates that both the April and January effects did not have a negative impact on momentum returns prior to the year 1998. Results so far in table 2.6 are not in line with table 2.5 and do not support the discussion according to which there appeared to be tax-loss selling in December and February. They are consistent, however, with Galariotis et al. (2007) who support no seasonality for UK momentum.

On the other hand, the 1999 – 2006 sub-period has only four months with statistically significant returns. While there are more than one calendar month with negative returns, they are all insignificant. The February through May calendar momentum returns are 5.88% (10% level of significance[30]), –0.39% (yet statistically insignificant), –4.61% (t-value is –1.81) and –1.67% (statistically insignificant), respectively. The negative insignificant returns prior to April (that is in March) indicate that both private and institutional investors could be offloading losers in February in light of March (for institutional traders) and of April (for individual and some institutional traders) tax-year ends. The negative returns in March are consistent with institutional traders readjusting their portfolios; and the April returns are consistent with both institutional and individual investors making adjustments to their portfolios. However, since the January momentum return is 2.52% (*t*-statistic 1.55), it is puzzling why the same phenomenon is not occurring for firms with tax-year ends at December – January as for those with tax-year ends at 31st of March. The conflicting behaviour of firms with different tax-year end applies to both the tax-loss selling and the window dressing activity of institutional investors.

To clarify this issue more, if Chen et al.'s (2007) suggestion that the new tax rules have taken away any incentives for tax-loss selling from corporations is correct, then the insignificant negative returns in March are not related to tax loss selling by institutional investors, but possibly to window dressing. However, it is not clear why this is not the case prior to 1998. In other words, why were not institutional investors engaging in window dressing activities prior to 1998? An alternative explanation could be that the 1998 Tax Act is intended to counter bed and breakfasting of shares; i.e., stocks repurchased within 30 days of selling are liable for taxation on the basis of the difference between the selling price and the repurchase price[31]. Therefore, to engage in a tax-loss selling activity, yet avoid the 30 days limitation period set by the tax authorities, individual investors would sell losers any time before the 5th of April and repurchase them after more than 30 days. Thus if the losing stock is sold on the 15th of March, an investor could only buy it back after the 15th of April to claim investment losses. Further, if the stock is sold on the 3rd of April, an investor could only buy it back

[30] Although the reported t-statistics is 2.22, it should be noted that the number of observations for this test is the number of the February calendar months between 1999 and 2006, i.e. 8 observations. And the t-statistics for a population of 7 ($n - 1$) at the 5% level of significance is 2.36.

[31] See Chen et al. (2007) for more on the bed and breakfasting regulation and its specifications.

after the 3rd of May to avoid tax. This explains the prolongation of the seasonal effect that continues up to May where momentum returns continue to be negative (–1.67% *t*-statistic –0.72).

Table 2.6

Holding sub-period returns by calendar months, 1984 – 1998 and 1999 – 2006

This table presents the momentum returns in each calendar month for the two sub-periods 1984–1998 and 1999–2006 (note that the first holding period starts from the very start of 1984), The split in the sample period indicates the date of the introduction of the new tax reform in 1998. Momentum portfolios are formed as in table 2.2. The ranking and holding periods are 6 months each. F_{All}, F_{Apr} and F_{Jan} test the null hypothesis that the momentum returns are equal among all calendar months, May through March and February through December, respectively. The F-*critical* values are reported in parentheses under each test. The *t*-statistics are reported in parentheses. The sample period is 1984–2006.

	Returns by calendar months	
6	1984 – 1998	1999 – 2006
Jan	0.64 (0.63)	2.52 (1.55)
Feb	0.63 (0.64)	5.88 (2.16)^
Mar	2.25 (2.07)^	-0.39 (-0.11)
Apr	1.35 (1.80)^	-4.61 (-1.81)
May	2.71 (3.77)†	-1.67 (-0.72)
Jun	3.36 (4.13)†	5.01 (1.92)^
Jul	3.69 (3.39)†	3.16 (1.80)
Aug	2.71 (2.26)*	4.08 (2.34)^
Sep	2.98 (2.88)*	6.95 (1.84)
Oct	2.61 (2.35)*	0.09 (0.04)
Nov	2.82 (3.53)†	0.08 (0.02)
Dec	1.32 (1.64)	4.82 (3.19)*
F-*statistic*$_{All}$	1.14 (F-*critical* at 10% 1.60)	1.90* (F-*critical* at 5% 1.90)
F-*statistic*$_{Apr}$	1.19 (F-*critical* at 10% 1.64)	1.30 (F-*critical* at 10% 1.68)
F-*statistic*$_{Jan}$	0.95 (F-*critical* at 10% 1.64)	1.98* (F-*critical* at 5% 1.95)

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

More specifically, as far as momentum is concerned, there appears to be no seasonality in the window up to 1998, but after that there are significant differences between the calendar months, except when April is excluded, meaning that any seasonal effect is mainly related to April. Particularly, the F-statistic is 1.30 (insignificant) when April is excluded and 1.90 (significant at 5%) when April is included. It is also evident that the April seasonal effect prevails over the January effect, which does not seem to have an effect in reversing momentum profits post 1998. This is consistent with the effect being mainly due to individual investors as in Ritter (1988) and with Chen et al. (2007) that the new Tax Act in 1998 has limited tax-loss selling activity by institutional investors but not by individual investors.

2.5.5 Event time study

In this subsection the profitability of the momentum strategy is monitored in event time. This section examines the behaviour of the momentum portfolio returns for the 36 event months following the formation date. This is done so as to see for how long the winners continue to outperform the losers and to see whether they reverse at some point in the post-holding period, and if so when. The drawback of a non-overlapping method in testing the long-term behaviour of momentum returns compared to this analysis is that long testing periods reduce the number of constructed portfolios. First, the event method is applied and the raw returns are investigated. Next, risk adjusted returns are estimated for each event month to examine the impact of the asset pricing models on holding period and post-holding period momentum returns. Given that momentum profits for the full sample period are significant for the different ranking periods used, and given the significance of the momentum strategy that is based on past 6 months returns, this subsection suffices to employ the momentum strategy with j equal to 6 months.

2.5.5.1 Raw returns

The results for the event time study are shown in table 2.7. The monthly average returns for the 12 months holding period are all positive. Except for month 12, the average returns are all statistically significant. In year 2, most event months generate negative returns that are not statistically significant indicating that the strategy does not tend to pick stocks that are systematically risky. In other words, if winners are systematically riskier than losers, then the former will unconditionally outperform the latter at any horizon (short-term and long-term). Given that losers significantly outperform winners at long-term holding periods, momentum strategies do not appear to be the result of cross-sectional variation in unconditional expected returns. It is also shown that the monthly average returns in the first half of year 3 are negative and statistically significant which implies that momentum returns tend to reverse for a short period during the post-holding period which is consistent with the findings of JT (2001) that a reversal representing an overreaction follows a short-term continuation in stock returns. The monthly average returns in the second half of year 3 are not distinguished from zero.

From the 2nd event month through the 15th event month, momentum profits decline monotonically from 2.61% (at the 1% level of significance) to –0.28% (statistically insignificant), respectively, showing that momentum profits are higher at shorter horizons. Momentum profits are significant at event month 11; however, the average return is 0.77% which is 3.5 times less than the 2nd event month return 2.61%. These findings have important implications to market traders. While short horizons momentum strategies earn more than medium horizons momentum strategies, short run strategies incur further trading costs. To clarify this matter, the higher trading costs feature offsets the benefit from the short horizons momentum strategies. For instance, if the holding period $k = 3$ is chosen, then in an overlapping framework, an investor would have three momentum portfolios opened at the same time. This means that every month the momentum investor has to close and open one third of total positions. Setting $k = 6$ implies that the investor has to close and open one sixth of total positions; i.e. less trading costs but less profits for the portfolios being held beyond the 3rd event month. In order to assess which strategy earns most after deducting trading costs, an estimation of the costs for rebalancing the momentum portfolio is needed. This matter is beyond the scope of this chapter; however, it will be assessed in chapter 4.

With respect to the 1st event month following the formation date, its average return is 1.83% (at 1% level of significance) which is 0.78% lower than the 2nd event month.

This indicates that there may be some sort of short run return reversal which is lowering the magnitude of first month momentum profits as suggested in previous subsections. Alternatively, it might simply be that the average return of the 1st event month is lower than the following 5 event months as shown in table 2.7. Chapter 4 looks at the weekly returns in more detail. However, the reversals, if any, are not large enough to reverse the overall sign of the monthly return.

Table 2.7

Momentum Returns using the event time study

At each month within the sample period, all stocks within the FTSE All Share are ranked based on their past 6 months returns. Stocks in the top decile are assigned to the winner portfolio, and those in the lowest decile to the loser portfolio. A zero-cost momentum portfolio is formed by buying winners and short selling losers. The monthly average returns and the cumulative returns of the zero-cost portfolios are presented for the 36 months following the formation period. *T* is the month after formation period. The Newey–West autocorrelation-and-heteroskedasticity consistent *t*-statistics are reported in parentheses. The sample period is 1983 to 2006.

T	Monthly Return	Cumulative Return	*T*	Monthly Return	Cumulative Return	*T*	Monthly Return	Cumulative Return
1	0.018357 (4.55)†	0.0183 (4.55)†	13	-0.00134 (-0.44)	0.1986 (5.02)†	25	-0.0081 (-3.79)†	0.1769 (3.20)†
2	0.026103 (6.69)†	0.0444 (4.92)†	14	-0.00274 (-0.99)	0.1958 (4.64)†	26	-0.01031 (-4.84)†	0.1666 (2.94)†
3	0.024544 (6.43)†	0.0690 (5.35)†	15	-0.00285 (-1.14)	0.1930 (4.34)†	27	-0.00845 (-4.05)†	0.1583 (2.73)†
4	0.022074 (6.11)†	0.0910 (5.72)†	16	-0.00249 (-1.03)	0.1905 (4.10)†	28	-0.01076 (-5.17)†	0.1477 (2.49)*
5	0.020004 (6.06)†	0.1110 (6.01)†	17	-0.00109 (-0.44)	0.1894 (3.92)†	29	-0.00773 (-3.39)†	0.1401 (2.31)*
6	0.019515 (6.19)†	0.1306 (6.28)†	18	-0.00152 (-0.62)	0.1879 (3.76)†	30	-0.00627 (-3.08)†	0.1340 (2.16)*
7	0.017541 (5.25)†	0.1481 (6.44)†	19	0.0020 (0.82)	0.1899 (3.72)†	31	-0.0031 (-1.43)	0.1309 (2.09)*
8	0.017486 (5.45)†	0.1656 (6.50)†	20	0.001379 (0.57)	0.1913 (3.70)†	32	-0.00152 (-0.72)	0.1295 (2.04)*
9	0.012747 (3.98)†	0.1783 (6.41)†	21	-0.00005 (-0.02)	0.1912 (3.69)†	33	0.001351 (0.59)	0.1308 (2.04)*
10	0.009394 (2.91)†	0.1877 (6.12)†	22	-0.00044 (-0.19)	0.1908 (3.64)†	34	0.002908 (1.52)	0.1336 (2.06)*
11	0.007794 (2.45)*	0.1955 (5.82)†	23	-0.00183 (-0.77)	0.1889 (3.55)†	35	0.000905 (0.45)	0.1344 (2.07)*
12	0.004407 (1.42)	0.1999 (5.46)†	24	-0.00403 (-1.81)^	0.1849 (3.41)†	36	-0.00177 (-0.91)	0.1327 (2.04)*

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

The cumulative return for year 1 is 20.0% with a monotonic increase in the cumulative returns from the formation date up to event month 12, which reduces to

18.49% and 13.2% at the end of years 2 and 3, respectively. The persistence of a high cumulative return at the end of year 2 is due to the low magnitude of returns in year 2 that is not high enough to offset the earlier profits. While JT (1993) report a cumulative return of 5.56% at the end of the second year, this finding (18.49%) is to some extent consistent with Ton and Honks (2003) who find an average of 0.49% over the first 24 months or 12% cumulative as reported for their 1977–1996 sub-period. This might imply some disparity in the long-term behaviour of momentum returns between the US and UK markets as regards the timing of the appearance of the negative returns. The momentum profits decrease by 1.5% in year 2 and 5.22% in year 3, whereas in JT (1993) momentum profits decline by 4% in the second year and 1.5% in the third year.

Significant reversals in monthly average returns during the post holding period suggest that the positive autocorrelation in the winner and loser portfolios are not permanent. During the event month 24 through event month 30, momentum returns are significantly less than zero. The evidence is in support of the behavioural hypotheses that return auto-correlations are followed by return reversals in the long horizon (see for example Daniel et al., 1998; and Barberis et al., 1998).

2.5.5.2 CAPM adjusted momentum returns

In this subsection risk adjusted momentum returns are estimated to examine the hypothesis of whether momentum profits are due to the systematic risk of the winners and losers stocks. Since this study uses the event time methodology, it provides an adequate comparison to previous studies using the same methodology in the US market. JT (2001) adjust raw returns to the conventional Capital Asset Pricing Model (CAPM) and the Fama French three-factor (FF3F) model. Furthermore, since this chapter looks at momentum returns over longer horizon, it is important to examine whether risk can explain either short-term continuations, long-term reversals, or both return anomalies documented and found in table 2.7. In particular, this chapter investigates whether the CAPM and FF3F models can capture the momentum returns at short and long horizons and compares the results with US evidence. This sub-section adjusts for risk using the Sharpe-Lintner CAPM and the FF3F model to see whether the observed abnormal returns are due to the selection of highly risky assets. Failure to capture the abnormal returns for the 36 months following the formation date indicates missing risk factors in the models and hence inadequacy of the models.

Table 2.8

Risk adjusted returns: CAPM alphas

At each month within the sample period, all stocks within the FTSE All Share are ranked based on their past 6 months returns. The zero-cost momentum portfolio is formed as in the previous table. The monthly average returns of the momentum portfolios for the 36 event months following the formation period are adjusted for risk using the CAPM: $R_{pt} = \alpha_p + \beta_p(R_{mt} - r_{ft}) + \varepsilon$. R_{pt} is the monthly average return of the momentum portfolio at month t, R_{mt} is the FTSE All Share value-weighted index return for month t, and r_f is the one month Treasury Bill rate for month t. α_p is the intercept from the regression. T is the month after formation period. The Newey–West autocorrelation-and-heteroskedasticity consistent t-statistics are reported in parentheses. The sample period is 1983 to 2006.

T	α_p	T	α_p	T	α_p
1	0.01861 (4.32)†	13	-0.0015 (-0.35)	25	-0.0080 (-2.94)†
2	0.0260 (6.04)†	14	-0.0029 (-0.76)	26	-0.0105 (-3.57)†
3	0.0238 (5.51)†	15	-0.0030 (-0.87)	27	-0.0088 (-3.27)†
4	0.0215 (5.12)†	16	-0.0032 (-1.01)	28	-0.0111 (-3.93)†
5	0.0195 (5.22)†	17	-0.0019 (-0.63)	29	-0.0080 (-2.81)†
6	0.0192 (5.46)†	18	-0.0019 (-0.67)	30	-0.0063 (-2.57)*
7	0.0169 (4.68)†	19	0.0011 (0.41)	31	-0.0032 (-1.25)
8	0.0158 (4.00)†	20	0.0003 (0.14)	32	-0.0015 (-0.67)
9	0.0115 (2.91)†	21	-0.0007 (-0.29)	33	0.0020 (0.77)
10	0.0084 (1.88)^	22	-0.0013 (-0.53)	34	0.0042 (2.02)*
11	0.0066 (1.44)	23	-0.0030 (-1.07)	35	0.0011 (0.49)
12	0.0039 (0.85)	24	-0.0040 (-1.43)	36	-0.0011 (-0.43)

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

First, the ability of the CAPM to capture the momentum profits is assessed. At each formation date within the sample period, the momentum portfolio is held for 36 months which are the 36 event months. This results in 36 time-series for each event month. To adjust for risk, for each calendar month t within the sample period, monthly momentum returns of the first event month after formation date are regressed against the FTSE All Share index that represents the market return. The risk-free rate –one month Treasury bill rate– is subtracted from the market return before regression and the difference is the market risk premium. The Jensen's alpha from the regression is the abnormal return of the momentum portfolio that is not captured by the market excess return. Table 2.8 reports the excess returns of the momentum portfolios (Jensen's alphas) for each of the 36 event months following the formation period.

The momentum profits are positive and statistically significant for the ten consecutive event months following the formation period after adjusting with respect to CAPM. Event month 11 is not statistically positive any more. Thus, the CAPM explains the momentum return of month 11 only of the holding period but fails to explain the short-term momentum profits in event months 1 to 10. Although the estimated alpha is significant, it is slightly smaller than the estimated raw returns in table 2.7 which indicates that CAPM partially explains the momentum profits of the ten event months after formation except for event month 1 where the Jensen's alpha from the CAPM (1.86%) is a bit larger than the raw momentum return (1.83%). The estimated alpha declines monotonically from event month 2 to event month 16. This decline leads to significant negative returns from event month 25 onwards. In fact 6 event months in the 3rd holding year period generate significant negative returns. These results are generally consistent with the earlier results and imply that systematic risk can neither fully explain momentum profits nor the return reversals in the post-holding period, consistent with Dissanaike (1997). Alpha is lowest for the event months 25 to 30 when its value is below –0.63% for these event months. Specifically the lowest estimated alpha is –1.11% (at the 1% level of significance) at event month 28 while the highest estimated alpha is 2.60% (at the 1% level of significance) for the 2nd event month. The results imply that there might be other omitted risk factors from the CAPM that could explain the realised anomalies. The following sub-section examines whether the augmented factors to the FF3F can explain the momentum anomaly.

2.5.5.3 Fama-French adjusted momentum returns

As mentioned earlier, the Fama French three-factor model, hereafter FF3F, was found unable to explain the abnormal momentum returns in previous studies. The expectation is that the common risk factors appended to the capital asset pricing model by Fama and French (1993) should explain only long-term reversals (Fama and French, 1996; JT 2001). The FF3F model consists of the market risk factor, SMB which is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML which is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks in addition to an intercept term that aims to catch unexplained risk. If the SMB and the HML factors are capable of capturing the abnormal returns from the momentum strategy then the alphas obtained from the regression should not be significantly different from zero. In comparison with previous US evidence, Fama and French (1996) show that their three-factor model could explain the long-term contrarian profits but not the short-term continuations in stock returns. JT (2001) find that the average FF3F-alpha over the first 12 months period are significantly positive (1.12%, t-statistic 5.95), whereas the average FF3F-alpha for year 2 and year 3 are negative and statistically insignificant. However, when JT (2001) restrict their sample to large firms the average FF3F-alpha remains significantly positive (0.89%, t-statistic 4.15). Galariotis et al. (2007) provide UK evidence and find that the FF3F could neither explain momentum nor contrarian profits. They also show that returns during the post-holding period of momentum strategies (years 2 and 3) remain significantly negative even after adjustment to the FF3F model.

Table 2.9 reports the alphas from the regression of momentum returns on the FF3F model. Momentum profits for months 1 to 11 do not disappear. This is in line with previous findings on adjustment to FF3F model. The positive significant FF3F alphas are not economically different from those of the CAPM alphas. Except for event month 1, 8 and 11, the FF3F alphas are slightly lower than the CAPM alphas, however the difference is not large enough to suggest that the additional size and B/M factors appended to the FF3F can significantly reduce momentum profits more than the CAPM.

Event month 12 generates positive, yet insignificant, FF3F adjusted returns as is the case with CAPM.

Table 2.9

Risk adjusted returns: Fama French three factor model

Portfolios are constructed as in table 2.8. The monthly average returns of the zero-cost portfolios for the 36 months following the formation period are adjusted for risk using the Fama French three factor model: $R_{pt} = \alpha_p + \beta_p(R_{mt} - r_{ft}) + \beta_{size}(SMB) + \beta_{B/M}(HML) + \varepsilon$. R_{pt} is the average monthly return of the momentum portfolio at month t, R_{mt} is the FTSE All Share value-weighted index return for month t, and r_f is the one month Treasury Bill rate for month t and SMB and HML are the additional FF factors. α_p is the intercept from the regression. T is the month after formation period. The Newey–West autocorrelation-and-heteroskedasticity consistent t-statistics are reported in parentheses. The sample period is 1983 to 2006.

T	α_p	T	α_p	T	α_p
1	0.0191 (4.47)†	13	-0.0005 (-0.13)	25	-0.0068 (-2.89)†
2	0.0253 (6.37)†	14	-0.0022 (-0.76)	26	-0.0086 (-3.56)†
3	0.0228 (5.67)†	15	-0.0017 (-0.69)	27	-0.0068 (-3.07)†
4	0.0213 (5.27)†	16	-0.0016 (-0.64)	28	-0.0094 (-4.22)†
5	0.0191 (5.24)†	17	-0.0003 (-0.14)	29	-0.0063 (-2.79)†
6	0.0191 (5.50)†	18	-0.0009 (-0.35)	30	-0.0049 (-2.28)†
7	0.0166 (4.26)†	19	0.0025 (1.02)	31	-0.0021 (-0.89)†
8	0.0159 (3.69)†	20	0.0017 (0.68)	32	$-9\text{x}10^{-5}$ (-0.04)
9	0.0114 (2.71)†	21	0.0007 (0.30)	33	0.0042 (1.63)
10	0.0087 (2.05)*	22	-0.0003 (-0.13)	34	0.0060 (2.74)†
11	0.0076 (1.85)^	23	-0.0019 (-0.73)	35	0.0030 (1.22)
12	0.0045 (1.11)	24	-0.0026 (-1.05)	36	0.0006 (0.24)

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

Moving on to the post-holding period returns, the results do not support the US evidence on the capability of the size and book-to-market factors to capture return reversals beyond the first year holding period. Contrary to the expectations, return reversals observed in the post-holding period are not explained by the additional risk factors. This result is similar to those of Galariotis et al. (2007) who find that FF3F risk adjusted average returns over 2 and 3 year periods are significantly negative for strategies based on past 4, 8 or 12 months ranking period[32]. Table 2.9 shows that in the 3rd year holding periods after formation, adjusted returns are significantly negative for 7 event months. The significant negative returns are also large in magnitude at some event months, reaching –0.94% (at the 1% level of significance) at event month 28. Again, the strongest reversals experienced are during the first half of the 3rd year similar to the results in tables 2.7 and 2.8. Therefore, profits may be genuine or there may be other omitted factors that could explain the abnormal returns at both the holding and the post-holding periods. As the purpose of this study is to examine the behaviour of momentum returns during the short-term to the medium-term horizons, testing the capability of the FF3F asset pricing model to capture long term reversals over 3 years holding period is beyond the scope of this study.

2.5.6 Market states and momentum returns

Previously, it has been shown that momentum profits tend to fade at longer horizons which results in minimising the duration of the momentum cycle. Moreover, the previous subsections show that neither systematic risk nor seasonal effects can explain momentum profits. Although the April effect is found robust in the post 1998 sub-period, other calendar months earn significant positive returns and the overall profitability of the momentum strategy is significant. It is appropriate to say that the fading phenomenon of momentum profits is not due to seasonal effects. Thus, what could be driving this new phenomenon of fading momentum profits over medium horizons?

The market state offers one possible explanation for the raised question especially of what has been happening in the recent years. Cooper et al. (2004) show that following an UP (DOWN) market, momentum strategies tend to generate positive (negative) returns. The period of 1998 to 2005 has experienced global economic and political crises that affected global financial markets as mentioned earlier. In addition, the results above show that momentum profits during the second sample sub-period (2000–2005), in table 2.3 (panel B) and in table 2.4, are not significantly positive

[32] Galariotis et al. (2007) do not rank stocks according to past 6 months; hence, the 4 and 8 months ranking periods are the nearest for comparison.

beyond six months holding period (except when j = 3). Moreover, the number of calendar months with significantly positive momentum profits has relatively decline during the 2000–2005 sub-period as shown by figure 2.3 especially around the dates when the market has undergone difficult times. This raises concerns whether bad market conditions has allegedly affected the profitability of the momentum strategies during that period which implies that momentum profits are conditioned to market states. In this sub-section an investigation of the association between market states and momentum profits is provided. The aim is to examine whether momentum profits depend on the state of the market as shown by Cooper et al. (2004) for the US market, and to understand why the profitability of the momentum cycle has been shortened post-2000. At each month t of the employed sample period, winner and loser portfolios are formed, and momentum portfolios are derived as described earlier. However, the formation period that is followed in this section is 6 months since it draws implications for strategies based on different formation periods. Therefore, all momentum portfolios in this section are based on their past 6 months returns as in the event time sub-section. In order to examine the effect of market states on the momentum portfolio formed at any month t, the event time methodology is employed. Particularly, the event methodology, as mentioned above, allows us to scrutinise the momentum returns in each event month. Therefore, it permits testing whether down markets affect the duration of the momentum cycles if not reversing the sign of momentum returns as suggested by Cooper et al. (2004). At any month t, an UP (DOWN) market is where the average return for the past x months of the FTSE All Share index is positive (negative). If the formation date for the momentum portfolio happens to follow an UP (DOWN) market, the expectation is that momentum profits are positive (negative).

Table 2.10 reports the results for momentum profits following UP and DOWN markets. Since there are 264 event months in this sample period, 264 momentum portfolios are formed. The past 36, 24 and 12 months before formation date of the momentum portfolio represent the market state, whereas the 36 time-series momentum returns corresponding to each event month of the holding period from the previous section are cumulated to form the holding period cumulative abnormal returns (CARs). CAR(1–3), CAR(1–6), CAR(1–9), CAR(1–12), and CAR(13–30) denote the cumulative abnormal returns for event months 1 to 3, 1 to 6, 1 to 9, 1 to 12 and event months 13 to 30 after portfolio formation date, respectively.

Table 2.10

Momentum returns and Market states – CAR

This table presents the momentum returns subject to market states. Momentum portfolios are formed as in table 2.7. The monthly average returns of the zero-cost portfolios are estimated when a month is skipped after the formation date. Non-negative (negative) average returns over the past 36, 24 and 12 months of the VW FTSE All Share Index represent UP (DOWN) markets. Reported below are the cumulative abnormal returns from the momentum portfolios across holding periods: months *t+1* to *t+3*, *t+1* to *t+6*, *t+1* to *t+9*, *t+1* to *t+12*, and *t+13* to *t+36*. The Newey–West autocorrelation-and-heteroskedasticity consistent *t*-statistics are reported in parentheses. Obs is the number of observation months for each strategy. The sample period is 1983 to 2006.

DOWN Market

	Obs	CAR(1-3)	CAR(1–6)	CAR(1–9)	CAR(1–12)	CAR(13–36)
Past 36	44	0.0814 (3.10)†	0.1169 (2.57)*	0.1583 (2.32)*	0.1632 (2.01)^	-0.0095 (-0.40)
Past 24	47	0.0919 (2.93)†	0.1488 (3.28)†	0.2101 (3.11)†	0.2394 (2.98)†	-0.0295 (-1.27)
Past 12	63	0.0995 (4.35)†	0.1617 (4.85)†	0.2252 (5.23)†	0.2618 (4.93)†	0.0101 (0.33)

UP Market

	Obs	CAR(1–3)	CAR(1–6)	CAR(1–9)	CAR(1–12)	CAR(13–36)
Past 36	220	0.0709 (7.35)†	0.1323 (9.69)†	0.1716 (9.11)†	0.1836 (7.49)†	-0.0835 (-3.36)†
Past 24	217	0.0685 (8.24)†	0.1256 (10.87)†	0.1605 (11.0)†	0.1674 (9.09)†	-0.0801 (-3.61)†
Past 12	201	0.0642 (8.81)†	0.1197 (10.61)†	0.1519 (9.71)†	0.1547 (7.94)†	-0.0966 (-4.37)†

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

The CAR(1–6) following a 12-months UP market averages at 11.9% (*t-statistic* 10.61) and that following a 12-months DOWN market at 16.2% (*t-statistic* 4.85). This indicates that momentum profits may not depend on market states as previously argued by Cooper et al. (2004). This holds true as well for market states based on past 24 or 36 months. However, while the results show that short-term return continuations of momentum strategies tend not to depend on past market states of 12, 24 or 36 months for the UK stock market, return reversals at medium-term horizons seem to be related to market states. Also, while momentum profits are reversed in their medium-term horizons following an UP market, they are indifferent to zero following a DOWN market. For instance, the CAR(13-36) for momentum portfolios is -9.66% (at 5% level of significance) following a 12-months UP market, whereas it is 1.01% and statistically insignificant following a DOWN market. These findings again hold true for all formations of market states whether they are based on 12, 24 or 36 months. These findings contradict those of Cooper et al. (2004) who find that momentum returns are negative following DOWN markets and are greater following UP markets; whereas this study suggests that momentum profits are not necessarily higher after UP markets and that they are not conditioned on market states. Furthermore, Cooper et al. (2004) find that the negative returns (in the long-run) exist despite the state of the market; whereas this study suggests that negative returns are significantly negative only following an UP market.

Table 2.11 reports monthly average momentum returns for event months 1-36 for strategies following both UP and DOWN markets in order to detect the point at which market states start to affect momentum returns. In the interests of brevity, results are reported only for market states determined on the basis of the past 12 months. The results from this part of the analysis are clearly in line with those in table 2.10. Generally, following both UP and DOWN markets, momentum profits are positive and significant for the first 11 months[33]. Following DOWN markets, momentum returns continue to be positive during the post-holding period until event month 22 (yet significant at event months 11, 14 and 18), and they turn negative at event month 23 onwards (except for months 32, 33 and 34 where they are positive but low and statistically insignificant). In contrast, following UP markets there are no months in which returns are significant and positive and there are twelve months in which returns are significantly negative during the post-holding period. The first significant reversal takes place on event month 13 (25) after an UP (a DOWN) market. Overall, there is much stronger evidence of return reversal following UP markets, than following DOWN markets. For example, following DOWN markets there are only four months in which returns are significant and negative and there are two months for which returns are significantly positive. It is apparent from figure 2.3 that following bad events, momentum returns become negative for three months or so after the event. Momentum calendar returns reverse immediately following these shocks, but the impact of these shocks does not persist long.

[33] While there are some months in which this is not the case, there is a clear pattern over these results.

Table 2.11
Momentum returns and Market states – Monthly Average Returns

At each month within the sample period, all stocks within the FTSE All Share are ranked based on their past 6 month returns. Stocks in the top decile are assigned to the Winner portfolio and those in the lowest decile to the Loser portfolio. A zero-cost portfolio is formed by buying Winners and selling Losers. The average monthly returns of the zero-cost portfolios are reported, when a month is skipped after the formation date, for the 36 months following the formation period after UP and DOWN markets. Non-negative (negative) returns of the VW FTSE All Share Index over past 12 months represent UP (DOWN) markets. *t*-statistics are reported in parentheses. The sample period is 1983 to 2006.

t	DOWN	UP	*t*	DOWN	UP	*T*	DOWN	UP
1	0.0333 (3.08)†	0.0238 (6.19)†	13	0.0109 (1.52)	-0.0070 (-2.51)*	25	-0.0092 (-2.22)*	-0.0106 (-4.26)†
2	0.0364 (3.4)†	0.0208 (5.61)†	14	0.0088 (1.68)^	-0.0065 (-2.33)*	26	-0.0082 (-1.89)^	-0.0085 (-3.55)†
3	0.0298 (2.82)†	0.0196 (5.78)†	15	0.0054 (1.05)	-0.0049 (-1.85)^	27	-0.0133 (-3.01)†	-0.0099 (-4.17)†
4	0.0239 (2.55)*	0.0187 (5.87)†	16	0.0038 (0.61)	-0.0026 (-1.05)	28	-0.0082 (-1.74)^	-0.0075 (-2.86)†
5	0.0225 (2.48)*	0.0185 (6.14)†	17	0.0082 (1.4)	-0.0045 (-1.78)^	29	-0.0053 (-1.42)	-0.0065 (-2.69)†
6	0.0156 (1.47)	0.0181 (6.32)†	18	0.0097 (1.95)^	-0.0004 (-0.14)	30	-0.0025 (-0.68)	-0.0032 (-1.24)
7	0.0210 (2.62)*	0.0163 (4.84)†	19	0.0058 (1.20)	$-8x10^{-6}$ (-0.003)	31	-0.0026 (-0.75)	-0.0011 (-0.44)
8	0.0270 (3.61)†	0.0082 (2.4)*	20	0.0014 (0.31)	-0.0005 (-0.21)	32	0.005 (1.23)	0.0001 (0.05)
9	0.0153 (1.73)^	0.0075 (2.34)*	21	0.0044 (0.95)	-0.0019 (-0.74)	33	0.0033 (0.94)	0.0027 (1.19)
10	0.0130 (1.64)	0.0061 (1.83)^	22	0.0006 (0.14)	-0.0026 (-0.94)	34	-0.0010 (-0.30)	0.0015 (0.64)
11	0.0149 (2.23)*	0.0011 (0.31)	23	-0.0020 (-0.42)	-0.0046 (-1.86)^	35	-0.0009 (-0.21)	-0.0020 (-0.91)
12	0.0085 (1.25)	-0.0044 (-1.33)	24	-0.0061 (-1.53)	-0.0087 (-3.45)†	36	0.0024 (0.57)	-0.0083 (-3.72)†

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

This confirms the earlier findings of no evidence of a systematic interaction between momentum profits and market states (over 1st year holding period), but clear evidence of market states impacting on return reversal (over 2nd and 3rd years post-holding period). Therefore, based on these findings, market states do not explain the fading phenomenon of momentum returns especially that momentum returns are larger and tend to persist more following DOWN markets.

2.6 Conclusion

The empirical tests carried out in this chapter provide some clarifications on the raised issues, yet some surprising findings also raised new questions. Momentum strategies are found profitable over a 12 months holding period for a sample comprising FTSE All Share constituents over the period 1983–2005. Despite controlling for thin trading, low priced stocks and size (exclusion of Fledging and AIM indices from the study), momentum profits, that are arguably associated to smaller and less traded stocks, do not disappear. In fact, the observed momentum profits in this study are larger than those in previous UK studies and are similar to those in Ellis and Thomas (2004). However, these profits tend to decrease monotonically as the holding period extends for various ranking periods. Nonetheless, the exclusion of low priced stocks, small stocks and thinly traded stocks could be argued to increase momentum profits rather than reduce them. However, further clarification regarding this issue is left for further research.

When partitioning the sample period to test whether momentum has faded in line with other anomalies, this study finds that in the post 1999 sub-period momentum strategies still deliver profits, but only for shorter investment horizons, up to 6 months. Extending either the ranking or holding period results in diminishing or eliminating momentum profits. The evidence that momentum profits persist only over short ranking periods and short holding periods in the 2000–2005 sub-period is new evidence with respect to the momentum phenomenon in the UK and supports similar US evidence by Henker et al. (2006). Of the 16 strategies implemented on the 2000–2005 sub-period, 5 strategies show significant evidence of momentum profits. There seems to be a pace in the learning process, with agents arbitraging away opportunities, that is shortening the life of the momentum cycle. This is argued to be the result of gradually increasing awareness of the market in line with Hong and Stein (1999).

The chapter aimed at investigating several possible sources that could explain momentum profits and the behaviour of momentum returns in recent years. According to its findings, seasonality can not rationalise UK momentum profits. However, the profitability varies across calendar months when April is not excluded. The January effect tends to disappear totally in momentum returns after the Tax Act of 1998 whereas the April effect is robust in the new tax regime generating significant negative returns. Negative momentum returns in April calendar months support UK evidence on tax-loss selling activities undertaken by individual investors (Draper and Paudyal, 1997). This study suggests that individual investors sell losers and repurchase them back at periods expanding to more than 30 days in order to avoid tax payments affecting the calendar momentum returns of the March and May – the adjacent calendar months to April.

Using the event time method shows that momentum profits continue until month 11 of the holding period but tend to reverse in the post-holding period over event months 24 to 30. After adjusting for risk, momentum profits over the first holding period year after the formation date do not occur to be affected; however, most of post-holding period event months (13 to 36) continue to reveal reversals. The intriguing evidence is that the FF3F does not eliminate return reversals in the intermediate horizons. The evidence on momentum profitability is not due to a failure of taking account of systematic risk

One possible explanation for the fading momentum profits in recent years is the difficult times that the UK market has undergone due to global bad events. This assumption is based on the findings of Cooper et al. (2004) that following distressed periods momentum returns are negative. However, following distressed periods (DOWN market) UK momentum strategies tend to earn higher profits than following periods of good conditions. Although there are negative momentum returns after crises and negative shocks, momentum profits bounce back very shortly and the overall profitability of a momentum strategy over the first holding period year (except for one month) is greater when following a DOWN market. This implies that shorter momentum cycles are not due to market states. In contrast, reversals do appear to be affected by market states. Thus, the findings that momentum profits are less evident in recent years, does not appear to be driven by market states, but rather it could be that such profits are now beginning to fade due to gradual market awareness of the momentum anomaly.

Another finding in this chapter is that losers contribute more to momentum profits than winners do. For the full sample period and for the partitioned sub-periods, it is shown that the underperformance of the loser portfolios is larger than the outperformance of the winner portfolios with respect to the return of the FTSE All Share index. This finding contradicts earlier evidence by JT (1993, 2001) that both winners and losers contribute about equally. Negative significant returns for the loser portfolios for both sub-periods contradicts the findings of Liu et al. (1999) and Hon and Tonks (2003) but is similar to the findings of Ellis and Thomas (2004). Short positions in the loser portfolios appear to drive momentum profits. This could be argued to be a disposition effect emerging from the tendency of investors to keep hold of their losing stocks. Hence, in less liquid markets or poor market periods and in certain markets (depending on regulations, costs, etc.) it may be difficult to put these strategies into effect as availability of stocks for short-selling reduces or even is not allowed. The disparity in the results between this study and earlier UK studies regarding the return to the loser portfolios should not be attributed to differences in the sample period. For instance, even after partitioning the sample period to end at around the same time with Liu et al.'s (1999) sample period, the losers' return in this study is significantly negative while in their study – which precedes this sample period by 5 years – losers earn positive returns. This means that if the disparity in the results is due to the additional 5 years in their sample period, the loser portfolios should have been earning very large positive return during that time to offset the negative returns in the 1983-1996 sub-period. Thus, it is suggested that the data sample (FTSE ALL Share) and the selection criteria followed in this study are mainly responsible for these results.

This chapter provides a comprehensive review of the profitability of momentum strategies in the UK market and investigates the variation of their profitability across different sub-periods, calendar months, and market states. However, recent evidence in the literature suggests that there are firm-specific factors that could partially explain momentum returns. Given that the sources of momentum profits in this study stem mainly from the losers' side, it is intriguing to see whether the same sources previously examined are mainly attributed to the firm-specific characteristics of losers. This is put forward because loser stocks are characterised by higher risk and larger trading costs. It is therefore essential to examine these issues and try to clarify the sources of momentum profits in the next empirical chapters.

2.7 Appendix:

- The size effect anomaly: Several studies have shown that small firms tend to outperform large firms Banz (1981) and Reinganum (1981). Recent studies lean towards the suggestion that the size effect has disappeared since it was first introduced (see Dimson and Marsh, 1999; Horowitz et al., 2000), where others go to claim that the size effect is mainly attributed to the January effect (Hawawini and Keim, 2000). Horowitz et al. (2000) find that controlling for the low priced stocks (penny stocks) eliminates the size effect.
- The January effect: this effect is attributed to the abnormal return of small stocks following tax year-end. Investors willing to realise substantial short-term capital losses at the turn of year for income tax purposes sell the depressed individual stocks near year-end which leads to a rebound in early January as investors repurchase these stocks to re-establish their positions (Roll, 1983; Reinganum, 1983). Other studies attribute the January effect to window dressing activity mainly driven by institutional investors (Haug and Hirschey, 2006) while Sias and Starks (1997) find larger January effects for firms with individual shareholders and conclude that the January anomaly is affected by tax-loss-selling activity.
- The initial public offerings (IPO) effect: The general view has been that IPOs tend to outperform in the short run, but then underperform in the longer run. (See for example, Ritter 1991; Ritter and Loughran 1995). To resolve this matter a study can eliminate individual stocks that might be straight out of an IPO.

3 Chapter Three: Industry, Volatility, Liquidity and the Cross-Section of Momentum Returns

3.1 Introduction

The first empirical chapter has shown that momentum profits persist despite attempts to control for risk, the low price effect, IPOs, and the small firm effect. Nonetheless, after the year 2000, the duration of the momentum cycle appears to be shortened. However, this is not related to the DOWN market states experienced in the post 2000 era. As a result the first chapter has attributed this to the possibility of an increasing market learning process. Moreover, there has been growing evidence showing that some firm-specific features influence the uncertainty about the value of the stock which, in turn, partially explain the cross-section of momentum returns. Thus, the pace of the market learning process about the intrinsic value of a stock could be affected by the firm-specific components and the uncertainty of the stock's value.

In Particular, Zhang (2006) shows that stocks with high information uncertainty, as measured by stock return volatility, generate higher (lower) returns for winner (loser) portfolios, which implies that momentum strategies based on high volatility stocks generate a larger return dispersion between winner and loser portfolios than a momentum strategy based on low volatility stocks. Having shown in the previous chapter that losers contribute more to momentum profits, it is motivating to see whether the larger momentum profits of high volatility stocks are mainly associated with losers who tend to be riskier. Zhang (2006) shows that information uncertainty contributes to the degree of underreaction which in turn affects the stock's future returns. High uncertainty implies more underreaction to news which is reflected in higher returns over the testing period. By contrast, lower uncertainty implies less underreaction because the news was mostly incorporated at the date of the news release which generates lower returns over the testing period. Zhang (2006) uses as a proxy of uncertainty the following measures: size, age of firm, return volatility, cash flow volatility, dispersions in analyst earnings forecasts and analyst coverage. His findings suggest that firm-specific characteristics could partially explain momentum profits by double-sorting individual stocks first on past returns and then on an information uncertainty proxy. Gutierrez and Prinsky (2007) show that momentum strategies yield different outcomes when based on raw returns compared to when based on idiosyncratic components of the return. More specifically, they find that ranking stocks according to past idiosyncratic components – after elimination of market risk and other market-wide components from raw returns – reduces the magnitude of momentum profits in the short term yet extends their durability. This raises concerns about whether total volatility and idiosyncratic volatility would consequently have different implications on information uncertainty and, hence, on momentum returns once the market wide components have been eliminated from the stock total volatility.

The impact of a market wide component on momentum returns is evident in momentum strategies based on common-factor portfolios – rather than individual stocks. Several studies show that momentum profits are significant when taking a long position in past winning industry portfolios and a short position in past losing industry portfolios. In fact, there is substantial literature on the impact of industry on momentum returns. Moskowitz and Grinblatt (1999) show that past winning industries continue to outperform past losing ones. Furthermore, they argue that, once adjusted for industry, momentum profits of individual stocks become negligible. Pan et al. (2004) find significant momentum profits in industry portfolios. Lewellen (2002) finds that size and book-to-market (B/M) portfolios exhibit momentum as strong as that in individual stocks and industry portfolios. He argues that since the size and B/M portfolios are well diversified and reflect systematic risk then momentum returns are attributed to macroeconomic factors. There is evidence of profitable industry momentum strategies in Europe (Swinkels, 2002), profitable industry-sector mutual funds (O'Neal, 2000) and significant higher momentum profits relative to industry growth (Safieddine and Sonti, 2007).

Evidence thus far suggests that there are two sources of momentum profits: the first is firm-specific factors and Zhang (2006) and Ang et al. (2006) provide evidence of differential momentum returns with respect to the volatility of stock returns; and the second is market wide components and in particular the industry effect (Moskowitz and Grinblatt, 1999; Pan et al., 2004; O'Neal, 2000; Swinkels, 2002). However, since stock volatility contains components of industry factors (Campbell et al., 2001; and Black et al., 2002), then adjusting for these components might reduce the dispersion in the cross-section of momentum returns caused by stock volatility. Therefore, and given the evidence that the role of market risk in determining the overall stock market volatility has diminished relative to sector risk, this chapter investigates whether under such a state of affairs the idiosyncratic components of the volatility would remain responsible for the cross-sectional dispersion of momentum returns and hence generate substantially different momentum profits. Specifically, this chapter aims to examine whether stock volatility plays a consistent role before and after adjusting for its industry component.

The issue of whether industry partially or entirely explains the effects of firm-specific characteristics on momentum profits has not yet been resolved from the findings of earlier studies. Using the return decomposition of Lo and MacKinlay (1990a), Lewellen (2002) finds that the negative cross-serial correlations among industry portfolios drive momentum profits, whereas Pan et al. (2004), using the same method, show that momentum profits are driven by the own autocorrelations in industry portfolios. In the latter case, where industry momentum returns are driven by their own-autocovariances, adjusting volatility to industry volatility would have a greater impact on the differential momentum return. Thus, there is a possibility for the industry effect to partially explain some of the firm-specific features and the cross-sectional return differences between high and low uncertainty stocks. While these two articles are portfolio-based studies, this study uses a different framework in investigating the above issues and aims to provide further evidence to the existing literature by projecting the industry effect on an individual stock-based study rather than a study based on industry portfolios. This study examines the cross-sectional dispersion of momentum returns with respect to volatility in an alternative way using two industry-adjusted volatility estimates.

However, to ensure that the dispersion in momentum returns between high volatility and low volatility stocks is not primarily caused by illiquid stocks, this study examines the impact of volatility on the cross-section of momentum returns on 3 portfolios with different levels of liquidity. Evidence from the literature on market micro structure suggests that volatility is positively related to illiquidity (Stoll, 1978) and this positive effect emerges from the fact that trading costs increase with volatility and therefore investors require higher returns on high volatility stocks. Furthermore, it is intuitive that limits to trade illiquid stocks delay the incorporation of new information into their prices leaving the prices uncorrected over a short period of time. This implies that controlling for the degree of liquidity should influence and possibly reduce momentum profits. To this extent, if momentum returns are due to underreaction (JT, 1993; Chan et al., 1996), it is important to examine whether a sample of highly liquid stocks would still generate momentum profits and whether large estimations of volatility are attributed to the liquidity effect by examining the volatility for each of the winner and loser portfolios across various levels of liquidity. Except for Ellis and Thomas (2003), who use the FTSE350 constituents, previous data sets of UK momentum studies do not focus on examining a highly liquid sample of UK stocks. This chapter goes a step further by examining the effect of the level of liquidity of the data set employed on momentum returns.

The main goal of this chapter is to examine whether industry can explain the dispersion of momentum returns with respect to volatility. There is an extensive number of studies providing evidence on firm-specific effects and market-wide effects on momentum profits, yet there has not been any study that investigates this proposition before. This is done by bringing together the assumptions from the studies abovementioned on firm-specific and market-wide effects, and builds on these assumptions to provide a further understanding on the role of each factor on momentum returns. Therefore, this chapter intends to tackle this challenge by examining the ability of market-wide factors to dominate the effects of a firm-specific feature on momentum returns. Furthermore, this study looks into the momentum profits of 3 portfolios representing various levels of liquidity and examines whether volatility of the winner and loser portfolios varies according to the level of liquidity. Since the role of industry might vary among high versus low liquidity stocks, the extent to which the industry factor can capture the volatility effect is examined among various levels of liquidity samples.

The next section reviews the literature with an emphasis on the relationship between momentum and each of industry and volatility. Section 3 describes the data samples and methodologies employed. Section 4 reports and discusses the results. And the final section concludes.

3.2 Literature Review

3.2.1 Overview

Sources for momentum profits remain unresolved until this day. The previous chapter shows that momentum profits for the UK market represented by the FTSE All Share constituents tend to disappear after year 2000 over holding or formation periods of more than 6 months. The findings from the previous chapter potentially suggest that increased awareness of market participants shortens the momentum cycle but does not eliminate momentum profits. The continuation of momentum profits has been given a considerable attention resulting in numerous studies investigating the possible sources of this anomaly.

There are two main approaches in the literature that attempt to explain the momentum effect: a) the behavioural approach that views this anomaly through models of human or market behaviour; b)the rational view or approach that examines cross correlations of stocks, or the correlation of stocks with micro/macro effects as explanations for momentum. Although there are various findings emerging from these studies it is possible to categorise these findings into 3 groups: the first suggests that momentum profits are a result of unconditional mean of stock returns; the second suggests that underreaction or a continuing overreaction to news is the reason for the short-horizon positive autocorrelations in stock returns which generates momentum profits; while the third assumes that cross-serial correlations among stocks helps to produce momentum profits.

In the following sections, this study provides a review of the literature that contains different perspectives on the correlation among stock returns and its implications on the momentum effect. The various findings and occasional contradictions in the literature concerning the sources of momentum profits reveal some gaps that this study addresses at the end of the literature review section.

3.2.2 Momentum in individual stock returns and portfolios returns

Following the seminal work of JT (1993) on the profitability of momentum strategies, a number of studies provide evidence of different sources of momentum profits. The great attention that momentum strategies have gained from academics could be owed to two main reasons: the persistence of momentum profits, and the inability of asset pricing models to fully capture momentum profits. Several papers show that momentum profits continue to exist years after being discovered (for example, Chan et al., 1999; JT, 2001 etc). Evidence of the persistence of the momentum phenomenon is also valid for international markets, for example Griffin et al. (2003) provide evidence from 30 countries up to 2000; Antoniou et al. (2007) provide evidence from the UK, France and Germany up to 2002; Ellis and Thomas (2003) and Galariotis et al. (2007) on the UK market up to 2003 and 2005, respectively. However, these studies do not examine the post-2000 period separately, as demonstrated in the previous chapter. On the other hand, asset pricing models have failed to explain momentum profits. Fama and French (1996), Avramov and Chordia (2006) and Griffin et al. (2003) show that risk models and macroeconomic variables can not fully explain momentum profits. Failing to explain momentum profits using risk models have driven financial economists to investigate the potential sources of these profits. While a group of researchers argue that it is firm-specific components that trigger the momentum effect in individual stocks, others claim that the stock's covariance with other stocks is mainly responsible for the observable momentum profits.

The former group argues that the short-term continuation in stock returns are associated with firm-specific components and that firms of uncertain future outcomes will gradually incorporate news into their prices generating a pattern of positive autocorrelation in stock returns[34]. These studies suggest that a momentum strategy would generate higher profits when conditioning on past returns and other factors associated with the delay in news incorporation rather than solely conditioning on past returns. There are several studies showing that the cross-sectional dispersion of momentum profits is attributed to idiosyncratic characteristics. Chan et al. (1999) show

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[34] See Chan et al. (1996) for momentum and gradual incorporation of information.

that momentum strategies based on past standardised unexpected earnings (SUE) or past analyst forecasts are profitable in addition to the conventional price momentum and that none of these momentum variables subsumes any of the others as each underreact to a different piece of information. Furthermore, they show that momentum strategies based on two classifications support their hypothesis; for example stocks within the winner portfolios (relative to past return momentum) which have high past SUE would generate higher returns over the holding period than if they had low SUE. In addition, Zhang (2006) shows that information uncertainty contributes to the underreaction to public information. He argues that if uncertainty delays the flow of information, where he defines uncertainty as "*the ambiguity with respect to the implications of new information for a firm's value*" (p. 105), then individual stocks with higher degrees of information uncertainty will obtain greater – in absolute value – returns over the holding period since news is not fully or completely incorporated. He uses six proxies for information uncertainty: firm size, firm age, analyst coverage, return volatility, cash flow volatility and dispersion in analyst forecasts. Avramov et al. (2007) find that credit rating attributes to momentum profits whereby low-grade firms but not high-grade firms earn significant momentum profits. Further evidence on firm-specific attributes to momentum profits is provided by Sagi and Seasholes (2007) who find that high revenue growth volatility, low costs, or valuable growth options contribute positively to momentum strategies.

On the other hand, Chordia and Shivakumar (2006) show that a macroeconomic component factor based on earnings momentum can capture the payoffs to price momentum strategies suggesting that since the earnings-based zero-cost portfolio is diversified, then price momentum is subsumed by a common factor that is related to the macro economy rather than idiosyncratic components of returns. More specifically, stock returns are assumed to covary due to the size effect, Book-to-Market effect or industry effect. In order to separate the impact of macro factors on contrarian profits from the firm-specific component, Lo and Mackinlay (1990a) decompose stock returns into 3 components: the stock return autocovariance, the cross-autocovariances across securities, and the cross-sectional variations in expected stock returns. The size relative portfolios suggest that the positive cross-serial correlations across securities dominates the negative autocorrelations in individual stock returns and that the positive autocorrelations in index returns are mainly due to cross effects (cross-serial correlations). Lo and Mackinlay (1990a) conclude that contrarian profits are due to the lead-lag effect and not due to the overreaction hypothesis (negative autocorrelations) of DeBondt and Thaler (1985). On the other hand, JT (1995) propose a model that separately examines the price reaction to common factors and firm-specific information. They argue that overreaction to firm-specific information always contributes to contrarian profits, whereas systematic overreaction to common factors can either increase or decrease these profits; and they show that stocks react with a delay to common factors but overreact to firm-specific information. Hence, they conclude that the lead-lag effect is limited to the price reaction to common factors. A corresponding paper by Chan (1993) indicates that the process of adjusting prices to reflect the true value in news leads to positive cross-serial correlations in stock returns. Chan (1993) argues that each market maker observes a noisy signal about one stock whereby this noisy signal contains a market-wide component as well as an idiosyncratic component. However, market makers can not determine the market-wide component from the specific one and can not instantaneously condition prices on signals of other stocks. As a result, Chan (1993) implies that if market makers condition on previous price changes of other stocks to retrieve more accurate information about the market-wide component, stock returns will be positively cross-autocorrelated.

However, the framework of Lo and Mackinlay (1990a) could also be applied to find the driving source of momentum profits among the decomposed components. Several studies apply this framework but their findings are inconsistent. Conrad and Kaul (1998) find that momentum returns are attributed to cross-sectional dispersion in expected stock returns. This finding is contradicted by Jegadeesh and Titman (2002) who argue that – after adjusting for small sample biases – momentum profits are driven by the autocorrelations in stock returns. The results from Chan (1993), Conrad and Kaul (1998) and Jegadeesh and Titman (2002) attribute short horizon positive continuation in stock returns to different components within the Lo and Mackinlay (1990a) decomposed model mentioned earlier.

The alternative approach of investigating the association of momentum returns with common factors is, therefore, through dividing the sample of stocks under assessment into a set of portfolios that could be size-based, B/M-based or industry-based. If the momentum effect is found significant in *the diversified* size, B/M or industry portfolios, then macroeconomic factors must be, at least partially, responsible for momentum profits. Moskowitz and Grinblatt (1999), hereafter MG, show that momentum profits in industry portfolios are as high as in individual stock returns. The large and diversified industry portfolios in MG (1999) paper suggest that momentum profits are attributed to a common factor, the industry effect. In addition, Lewellen (2002) shows that diversified industry, B/M and size portfolios also exhibit significant momentum profits. The latter argues that "macroeconomic factors, not firm-specific returns, must be responsible for size and B/M momentum" and that underreaction seems unlikely as an explanation to momentum profits resulting from industry, B/M or size portfolios.

The above evidence suggests that there are various sources for the momentum effect. Momentum profits could be driven by the cross-serial correlation among stocks; that is, the lead-lag effect between large and small stocks. However, since the lead-lag effect is mostly evident between large and liquid stocks leading small and illiquid stocks, it is vital to examine the persistence of momentum strategy after controlling for the trading frequency of the stocks. This would clarify whether momentum profits persist among stocks that are frequently traded and are less exposed to the lead-lag effect.

3.2.3 Volatility and Momentum returns

As briefly mentioned above, Zhang (2006) finds that since higher information uncertainty about the value of a firm exacerbates the psychological biases of an investor, and since greater underreaction (which is due to psychological biases) generates larger return continuation, then when there is more uncertainty there will be more underreaction (or slower response to information) and hence larger momentum returns. In his paper, Zhang (2006) presents stock return volatility as a proxy for information uncertainty, where volatility is "*the standard deviation of weekly market excess return over the year ending at the portfolio formation date*" (p. 110), and shows that stock return volatility plays a significant role in the cross-section of momentum portfolios' returns. Using an analogous methodology, Ang et al. (2006) sort stocks into quintiles on the basis of past returns and then within each momentum quintile they sort the stocks into 5 portfolios on the basis of idiosyncratic volatility[35]. The findings of Ang et al. (2006) conflict with those of Zhang (2006). While low idiosyncratic volatility firms earn more than high idiosyncratic volatility firms in the loser portfolio, the same phenomenon occurs in the winner portfolio in Ang et al's results. In other words, Ang et al. (2006) find that the average cross-sectional return of high volatility stocks is always lower than the average cross-sectional return of low-volatility stocks even after controlling for the momentum effect. This essentially contradicts the proposition of Zhang (2006) that higher volatility stocks imply higher underreaction and therefore they earn less in the loser portfolio but more in the winner portfolio. Although Ang et al. (2006) show that stocks with high sensitivities to aggregate volatility risk earn on average lower returns than stocks with low sensitivities to aggregate volatility, the exposure to aggregate volatility risk cannot explain the difference in returns between high and low idiosyncratic volatility portfolios. Therefore, it is crucial to examine the cross-sectional effect of volatility on momentum returns in an out-of-sample using the double sorting methodology in the above studies.

However, there is evidence that high volatility is positively related to illiquid stocks (Stoll, 1978) which requires that the examination of the cross-sectional effect of volatility should be approached with considerable attention to the level of liquidity. Furthermore, several studies show that illiquidity affects the cross-section of stock returns positively (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chalmers and Kadlec, 1998) and that while expected illiquidity has a positive significant effect on ex-ante stock excess returns, unexpected illiquidity has rather a negative significant effect on contemporaneous stock returns (Amihud, 2002). Although the principal aim of this study is not to investigate the effect of illiquidity on stock returns, it is essential to consider the potential consequences that illiquidity might have on the relation between volatility and momentum returns. This step ensures that higher returns are not due to thinly traded stocks (which are usually small stocks). In fact, Amihud (2002) argues that excess returns in small stocks over time are partially due to illiquidity.

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[35] Ang et al. 2006 use idiosyncratic volatility to refer to the standard deviation of the error term from the FF3F adjusted stock returns.

To ensure that the results from testing the cross-sectional effect of volatility are not severely contaminated with illiquid stocks that are driving the differential momentum returns, the tests are repeated for various samples representing different levels of liquidity. The frequency of trading would represent the liquidity level for a stock to be included in any sample. The data set from the previous empirical chapter represents one of the three liquidity samples in this chapter. Additional liquidity constraints are applied to the previous data set to form the other liquidity samples. This is done to eliminate a set of stocks that are usually more expensive and difficult to trade. This would certainly result in a smaller sample, yet more practical to trade. The implications of controlling for thinly traded stocks for fund managers is that such a sample with a higher level of liquidity might sacrifice some of the risk diversification advantages for more feasibility in the implementation process of constructing and liquidating momentum portfolios and for more information visibility in the process of learning about the value of the stocks.

3.2.4 Industry and Momentum returns

The impact of the industry effect on momentum strategies has been widely examined in the literature. MG (1999) provide evidence that momentum profits are the result of past winner industry-portfolios outperforming past loser industry-portfolios. Furthermore, they show that momentum profits in individual stocks become negligible after adjustment for industry; however, industry momentum strategies remain significantly profitable after adjusting for size, Book-to-Market, and individual stock momentum. Furthermore, and similar to MG (1999), Pan et al. (2004) provide evidence of industry momentum profits by buying past winner industry portfolios and selling short past loser industry portfolios. Using the decomposition suggested by and Lo and Mackinlay (1990a), Pan et al. (2004) show that industry momentum profits are mainly driven by the own-autocorrelations in industry portfolio returns.

However, alternative tests and results from other papers make it less possible to claim that momentum profits are solely attributed to industry momentum returns and that firm-specific components play no role in generating momentum profits. Asness et al. (2000) argue that although industry portfolio strategies generate momentum profits, there are significant momentum profits within-industry; i.e. the predictable power of past returns in individual stocks can not all be captured by the industry effect. The disparity in the results of the two studies is, according to Asness et al. (2000), partly driven by two factors: firstly, the difference in industry definitions, whereby MG (1999) define a set of 20 industries based on two digit SIC codes, while Asness et al. (2000) use a set of 48 industries based on 4 digit SIC codes; secondly, is that failing to skip a month between the portfolio formation period and the holding period will reduce the within-industry effect but not the across-industry effect. Evidence from the European stock markets supports US evidence of the impact of industry on momentum returns. Swinkels (2002) shows that industry momentum strategies in Europe are more profitable than in the US market. Swinkels (2002) also finds some evidence of the lead-lag effect across markets, whereby the US stock market leads European stock markets, but not the other way round. Scowcroft and Sefton (2005) show that while industry momentum drives momentum profits of large-cap stocks, firm-specific components influence momentum profits at the small-cap level. Another method of exploiting momentum profits is presented by O'Neal (2000) which entails buying industry-sector mutual funds of previous best-performing industry funds and selling those of previous worst-performing industry mutual funds over intermediate horizons. Varying the ranking period, holding period or the number of industry mutual funds in the top and bottom portfolios does not affect the industry mutual funds momentum profits observed by O'Neal (2000).

On the other hand, stock volatility is also correlated to the volatility of the industry that the firm belongs to. Campbell et al. (2001) identify 3 components of volatility: the market, the industry and the firm components. As a matter of fact, there is evidence from the UK market that much of the volatility in the stock market could be attributed to sectors or sub-sectors and that the role of market risk has diminished as the driving force for overall volatility (Black et al., 2002). Morana and Sawkins (2004), however, find that industry-specific factors, rather than market factors, are the determinants of the overall volatility level for the Gas, Water and Electricity industries in the UK market.

To this extent, it can be seen that more research is needed to clarify the raising concerns from the above review of literature. Specifically, the ambiguity in determining the driving forces behind momentum profits demands further research. Since momentum profits are influenced both by firm-specific features and macro factors, and since the volatility of a stock contains components related to that of its industry, it is possible that the macro components within the stock volatility are responsible for the differential momentum returns. Therefore, by double sorting the stocks into past returns and then industry-adjusted volatility, the return differential between high volatility stocks and low volatility stocks (holding constant the past returns) is attributable to the idiosyncratic component of volatility. This chapter investigates whether volatility could still explain variations in the cross-section of momentum returns after controlling for the industry component. By specifying the responsible term that influences momentum profits, this study will clarify the unresolved issue of whether the sources of momentum profits are solely attributed to firm-specific features or simply reflect common factors residing within variables such as volatility.

However, given evidence that industry momentum drives large-cap and individual-stock momentum drives small-cap stocks, it is not very clear whether adjusting volatility to the industry effect would have the same impact on all stocks. In other words, if firm-specific factors primarily influence the profitability of momentum strategies of small and less liquid stocks, then the industry factor would have a lesser impact on capturing the volatility effect on the cross-section of momentum returns in individual stocks. The impact of the industry factor on capturing the volatility effect is expected to increase with large and highly liquid stocks. As a result, it is crucial to examine the industry effect over various liquidity levels to see whether industry-adjusted volatility would have the same effect on momentum returns in varying the level of liquidity of the stocks employed.

3.3 Research Questions and Hypotheses:

The addressed gaps are ordered in sequence of discussion in the results section below. From the review of the literature above, the following gaps are identified:

- The profitability of UK momentum strategies with respect to various levels of sample liquidity
- The consequences of controlling for thinly traded stocks on the volatility of the winner and loser portfolios

- Investigating the impact of stock volatility on the cross-section of momentum returns for UK market and the implications of trading infrequencies on that relationship
- The industry effect and the possibility for it to induce the dispersions in momentum returns

The proposed hypotheses are based on the documented gaps observed in the literature. First, it is argued above in the literature review section that illiquidity affects the cross-section of stock returns positively. While previous UK momentum studies have employed various data sets, this study proposes to assess the profitability of momentum strategies using various levels of the "trading frequency" control variable.

Hypothesis 1: The Profitability of momentum strategies is not affected after controlling for thinly traded stocks of the FTSE All Share Constituents.

Second, based on the empirical evidence from the previous chapter that losers contribute more to momentum profits than winners, it is important to examine whether this is related to the relatively higher risk of the loser stocks by comparing the volatility of both the winner and loser portfolios.

Hypothesis 2: The volatility of the loser portfolios is not significantly different from that of the winner portfolios.

Furthermore, previous studies show that volatility rises with illiquidity. To ensure that the winner and loser portfolios in this study are not mainly high volatile stocks, this study examines and compares the volatility of the winner and loser portfolios among the 3 various levels of liquidity samples.

Hypothesis 3: The level of risk of the winner and loser portfolios change as a result of excluding thinly traded stocks from the sample data.

Contradicting findings are found between Zhang (2006) and Ang et al. (2006) regarding the momentum returns of high and low volatile stocks within the winner portfolio. The former argues that higher volatility implies higher underreaction and hence greater – in absolute value – returns, whereas the latter find that low volatility stocks outperform high volatility stocks regardless of past return. This chapter undertakes an out-of-sample test for the impact of volatility on momentum returns.

Hypothesis 4: The cross-sectional dispersion of momentum returns with respect to stock volatility is significantly different from zero.

If the industry component within stock volatility is responsible for the variations in cross-sectional momentum returns, then industry-adjusted volatility should have no effect, on the cross-sectional dispersion of momentum returns.

Hypothesis 5: Adjusting the stock's volatility to the industry volatility reduces the dispersion of momentum returns between high and low industry-adjusted volatility stocks.

3.4 Data and Methodology

3.4.1 Data

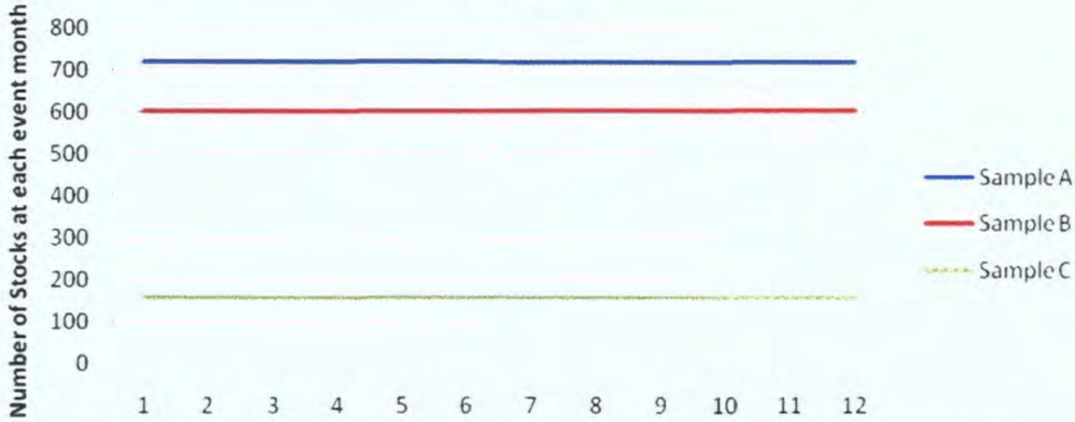
The data sample consists of all stocks belonging to the historical FTSE All Share Constituents. The first momentum portfolio is formed on January 1983 and the last on December 2004, however, the sample period of stock returns goes up to 2005. A description of the FTSE All Share Constituent has been already introduced in the previous chapter. In this chapter the same sample is employed to draw implications on the most profitable momentum strategies found in the previous chapter. The FTSE All Share Constituents exist on DataStream as of March 2001. Historical constituent lists prior to that date were provided by FT. As in the previous chapter, company names from FT historical lists are matched with DataStream. After matching the companies' names, all data variables are downloaded from DataStream using the DataStream codes for companies.

Similar restrictions were applied to the sample data as in the previous chapter; low priced stocks[36] and stocks with less than 12 months return observations were excluded from the study. However, to further control for the illiquidity effect, this chapter emphasizes the issue by examining momentum profits on 3 levels of liquidity. By setting additional constraints for the inclusion of stocks in the highly liquid samples, this study will control the nonsynchronous effect among stocks of different levels of liquidity. Three samples are constructed: the first excludes all stocks that are not traded over 3 consecutive months during the formation period[37], the second (third) sample excludes all stocks that are not traded in each month (week) during the formation period. No doubt that the average number of stocks in the last sample or the weekly traded stocks sample will substantially drop due to the limitation of stocks that are highly liquid which could be thought of as the sample with the large-cap stocks. For clarification, the first, second and third samples which correspond to the whole sample, the monthly traded stocks sample and the weekly traded stocks sample, respectively, will henceforth be referred to as sample A, sample B and sample C.

It is important to ensure that all samples employed are large enough to test their statistical inferences. However, as some stocks tend to die, especially small stocks, the number of stocks within the portfolio is expected to decrease throughout the holding period. This phenomenon is noticeable in sample A, which contains more illiquid stocks relative to samples B and C. The pattern representing the number of stocks during the testing window for sample A is shown in the previous chapter and is reproduced here in figure 3.1, however for the sample period 1987–2004. The average number of stocks decreases slightly from 720.87 in month 1 to 717 in month 12. By contrast, the average number of stocks does not change during the testing window for samples B and C which indicates that monthly and weekly traded stocks are hardly ever delisted. While the average number of stocks during month 1 is 601.27 (158.15), it becomes 601.16 (158.11) for sample B (sample C) in month 12, respectively. This implies that monthly traded stocks are not among the stocks that are exposed to delisting or M&A. Perhaps, these findings will have important implications for the feasibility of momentum trading.

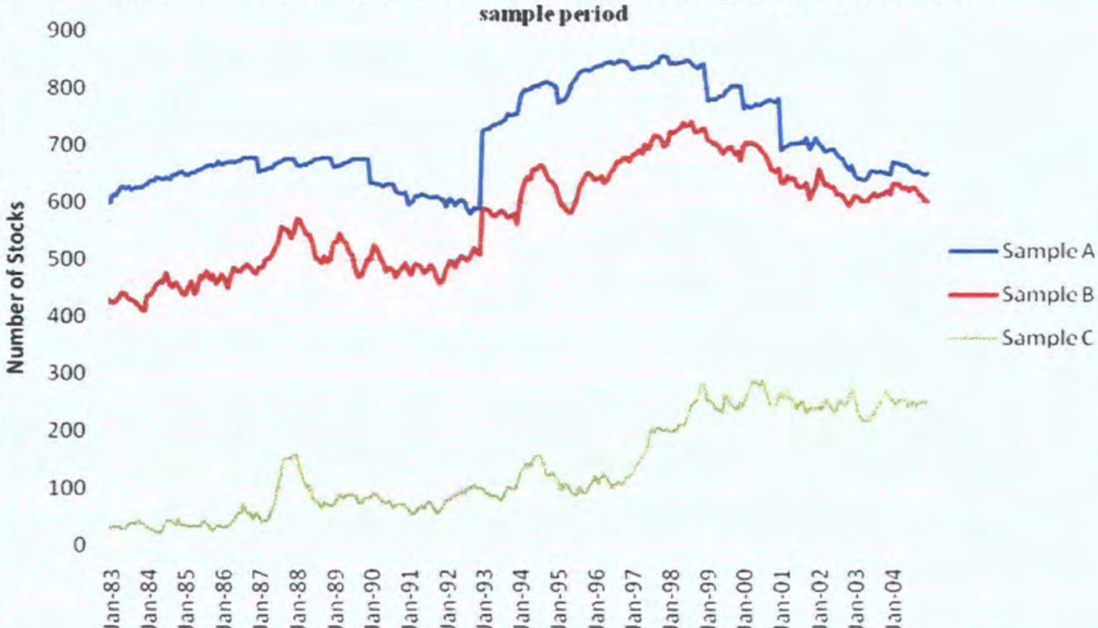
[36] Stocks that are priced less than 30 pence on the formation date are excluded from the sample. This requirement is argued by Nagel (2001) to be proportional to eliminating stocks below $5 in the US samples.
[37] The first sample is the same sample that is used in the previous chapter.

Figure 3.1
Average number of stocks during the 12 months holding period following portfolio formation



The patterns in this figure represent the average number of stocks for 3 liquidity samples (samples A, B and C) during the 12 months holding period after the formation date of the portfolio. Sample A includes all stocks within FTSE All Share at the formation date of the portfolio excluding stocks that are priced below 30 pence; stocks that do not have 12 months return observations prior to the formation date and stocks that are not traded for 3 consecutive months during formation period. Sample B (C) excludes from sample A all stocks that are not traded in each month (week) during the past 6 months. At each month *t* of the sample period, the number of stocks meeting the criteria is obtained. This results in 216 observations for each month of the holding period. The average number of stocks at each holding period month is determined for all samples.

Figure 3.2
The number of stocks at month 1 holding period for all liquidity samples during the sample period



This figure depicts a chronological representation of the number of stocks over the sample period January 1983 – December 2004 for each of the samples A, B and C identified above. The stocks that meet the criteria are counted at the formation date of the portfolios.

Next, it is also crucial to see whether the number of stocks varies over the sample period in the 3 liquidity samples. Since the number of stocks in any of the samples does not change dramatically during the holding period of the portfolio (as shown in the previous chapter), then this study will suffice to examine the variation in number of stocks over time by looking at the number of stocks in the 1st month holding period for each of the 216 portfolios. Figure 3.2 depicts the variation in the number of stocks for each sample over time. In other words, figure 3.2 represents a rough picture on the level of liquidity of stocks in the FTSE All Share Constituency. The number of weekly traded stocks is generally increasing over time and exceeds 100 only after 1988 and exceeds 200 after 1998. Table 3.1 shows the maximum, minimum, median and average number of stocks for samples A, B and C. The number of stocks for sample C is mainly low for the years 1983 to 1986[38] implying that there are few frequently traded stocks during this time of the sample period which dictates that the sample period begins as of 1987. The average number of stocks is 720.87, 601.27 and 158.15 for samples A, B and C, respectively.

Table 3.1

Number of stocks in holding period month over the sample period 1987 – 2004

This table presents the number of stocks within the samples employed in this study during the sample period July 1987 – December 2004. At each month t during the sample period, all stocks within the FTSE All Share constituent are counted after eliminating stocks that do not meet the required criteria. Stocks that are priced below 30 pence or that do not have return observations over the last 12 months are excluded. Sample A excludes stocks that are not traded for 3 consecutive months over the past 12 month period. Sample B excludes stocks that are not traded at least once every month over the past 6 months. Sample C excludes stocks that are not traded at least once every week over the past 6 months.

	Number of stocks			
	Maximum	Minimum	Median	Average
Sample A	856	580	695	720.87
Sample B	742	459	613	601.27
Sample C	288	40	133	158.15

[38] The number of stocks reaches 50 in the year 1986 as shown in Figure 3.2.

Table 3.2

Industry Types and number of companies per industry

This table shows the classifications followed in this study of the industry sectors in the UK Stock Market according to the Financial Times. At the beginning of each year, each company is assigned to its relevant industry and the number of companies in each industry is averaged among all years. Interim changes of industry type take effect at the turn of the year only. The Type of Industry Sector, Mean and Median are shown below. The zero values in the Median column indicates that over half the sample period, no companies belonging to that industry that were included in the study because that particular type of industry had not been introduced. The sample period is 1987 to 2004.

TYPE OF INDUSTRY	MEAN	MEDIAN
AEROSPACE & DEFENCE	4.052632	0
AUTOMOBILES & PARTS	11.42105	13
BANKS	9.736842	9
BEVERAGES	19.73684	22
CONSTRUCTION & MATERIALS	52.31579	57
CHEMICALS	19.78947	21
GENERAL INDUSTRIES	25	27
INDUSTRIAL ENGINEERING	48.57895	54
ELECTRONIC & ELECTRIC EQUIPMENTS	33.89474	37
ELECTRICITY	7.736842	7
FORESTRY & PAPER	15.31579	15
FOOD & DRUG RETAILERS	14.31579	16
FOOD PRODUCERS	21.73684	23
GENERAL RETAILERS	51.36842	47
HEALTH/CARE EQUIPMENTS & SERVICES	16.26316	14
LEISURE & HOUSEHOLD GOODS	11.05263	12
TCH HARDWARE & EQUIPMENTS	3.578947	0
NONLIFE INSURANCE	16.10526	16
EQUITY INVESTMENT INSTITUTIONS	106.6842	117
TRAVEL & LEISURE	31.73684	30
LIFE INSURANCE	7.210526	7
MEDIA	37.10526	38
MINING	3.631579	4
OIL & GAS PRODUCTION	15	15
PERSONAL GOODS	15	19
PHARMACEUTICAL & BIOLOGICAL	9.473684	11
REAL ESTATE	42.89474	43
SOFTWARE & COMPUTER SERVICES	12.31579	0
GENERAL FINANCE	31.68421	31
SUPPORT SERVICES	35.94737	37
INDUSTRIAL METALS	3.947368	1
TOBACCO	1.947368	2
INDUSTRIAL TRANSPORTATION	17.68421	17
FIXED LINE TELECOMMUNICATIONS	7.052632	7
GS/WT/MUL UTILITIES	8.947368	10

This chapter examines the industry effect on firm-specific components as sources of momentum profits. Therefore, it is essential to identify the types of industries to be considered in the assessment. This study follows the Financial Times classification of industries for the UK stock market. FT classifies stocks into 35 individual industries. Asness et al. (2000) argue that their classification of stocks into 48 industries provides evidence of momentum profits within-industry and that the classification of MG (1999) into 20 industries might have driven the results in favour of the prevailing impact of macro effects over the micro effects. The following classification used in this chapter lies in between both of these studies, however, since the number of stocks in the US market exceeds by far those in the UK market, it is more appropriate to consider a smaller number of industry types than that of Asness et al. (2000) as this research intends to capture all industry-related components of the individual stock returns.

The FT classification of industries is matched with DataStream and the weekly Price Index PI for each industry goes back to January 1986 in DataStream. This study follows the Financial Times sorting of stocks into the different types of industries. It should be noted that industries with few firms do not affect the results of this study. Since this study is stock-based rather than portfolio-based, then the absence of an industry at some point of time in the sample period means that there are no individual firms belonging to that industry sector in the data sample at that point of time. This study aims to examine the industry effect on the momentum and volatility of individual stocks that are eligible for inclusion in the data samples, and hence, it is different from portfolio-based studies that look at the outperformance of one industry over another which necessitates a large number of stocks within each industry.

3.4.2 Methodology

3.4.2.1 Constructing the momentum portfolios

The momentum portfolios are constructed as described in the previous chapter for overlapping portfolios. At the beginning of each month t, all stocks are ranked based on their past j months returns. Then, the top stocks are assigned to the winner portfolio and the bottom to the loser portfolio. The momentum strategy entails forming a zero-cost momentum portfolio that buys winners, short sells losers and closes both positions after k months. Hence, similar to the method of JT (1993), at any month t, the winner portfolio consists of the winning stocks at month t as well as the winning stocks at the past $k - 1$ months. The loser portfolio is formed in a similar manner. For a given calendar month, k momentum strategies remain open at the same time. The overlapping methodology used in this chapter is, thus, similar to the one in the previous empirical chapter.

In examining the persistence of momentum profits against liquidity in individual stocks, the momentum portfolio consists of the top and bottom deciles (winners and losers, respectively) of the stocks ranked on their past j returns. Later, when the study investigates the impact of stock volatility on momentum returns, double sorting is required which necessitates that the winner and loser portfolios consist of the top and the bottom quintiles. Each quintile is further divided into 3 equal sub-portfolios relative to the stocks return volatility. The quintile procedure is followed with the double sorting to guarantee a sufficient number of stocks within the sub-portfolios. The momentum return of each sub-portfolio is determined. This enables a comparison between the momentum return of high-volatility sub-portfolios and low-volatility sub-portfolios. It also enables a comparison of a momentum strategy that buys (sell short) the high-volatility winners (losers) with a momentum strategy that buys (sell short) low-volatility winners (losers). This methodology is presented by Zhang (2006) and Ang et al. (2006) to test the impact of information uncertainty (in this case stock volatility) and the impact of idiosyncratic volatility on momentum returns.

3.4.2.2 Computation of momentum profits

To determine momentum profits, the returns to the winner and loser portfolios are estimated and the losers' return is subtracted from the winners' return. The return to the winner (loser) portfolio is the equally weighted return of all stocks within the winner (loser) portfolio. Returns to individual stocks are estimated as continuously compounded returns using the 1st difference of the natural logarithm of monthly prices. Since the results from the previous chapter indicate similar momentum profits from both overlapping and non-overlapping strategies, this chapter will focus only one, namely the overlapping strategy, when testing the proposed hypotheses. At each month t, all stocks that meet the criteria to be included in any of the pre-defined samples A, B or C are ranked based on their past j months returns and held for k months. As stocks are held for k months then the momentum strategy at any month t will consist of k opened positions simultaneously. The return of the momentum portfolio at month t is therefore the average return of k positions formed between months $t - k + 1$ and t

$$\overset{J\times K}{R}_{Momentum,t} = \sum_{f=t-k+1}^{f=t} \frac{R_{Winner,f} - R_{Loser,f}}{k} \qquad (3.1)$$

where $R_{Momentum,t}$ is the momentum profit at month t for k opened positions; $R_{Winners,f}$ and $R_{Losers,f}$ are the equally weighted mean monthly returns at month t for the corresponding winner and loser portfolios with holding period starting at month f, respectively. The time-series average of all the momentum profits represents the mean monthly profit of the momentum trading strategy $J \times K$.

Building on the results from the previous chapter, and in an attempt to investigate the persistence of momentum profits after restricting the sample data to the highly liquid stocks, only the two most profitable strategies from chapter 1 in addition to the 6×6 strategy are employed to test the proposed hypotheses. This is so because if momentum profits tend to disappear in the two most profitable strategies then it is almost certain that they will disappear in other less profitable strategies. Therefore, by employing these strategies, this study examines whether momentum profits persist in the most profitable strategies for highly liquid stocks. The 6x6 strategy is being employed to provide relevant comparison with the literature as it is the strategy most researched and adopted[39]. If results are driven by the lead-lag effect, it should be shown on the beginning of the holding period as the effect of the lead-lag is over a short period. Therefore, this study looks at more than one month holding period to see whether momentum profits persist beyond the impact of the lead-lag effect in comparison with studies that employ the double sorting methodology over a 1 month holding period.

Most studies on momentum consider skipping a month between the formation date and the holding period to control for potential microstructure effects and short-run

[39] JT (2001), Cooper et al. (2004) and MG (1999) limit their testing to the 6x6 for its representativeness.

return reversals (see for example JT, 1993). In the previous chapter, both momentum strategies that skip and do not skip a month between formation and holding period reveal similar results; hence, and for the interest of brevity, only strategies that skip a month are demonstrated when testing for the profitability of momentum strategies among the various samples. In a strategy that skips a month between the formation and the holding period, stocks are ranked based on their past j months returns spanning from $t-j+1$ to $t-1$ and the holding period for the momentum portfolio spans over $t+1$ to $t+k$, skipping the formation month t.

3.4.2.3 Estimating volatility

As one of the objectives in this study is to determine whether the estimated volatility of the winner stocks versus the loser stocks could vary with the type of volatility measure, it is crucial to examine the volatility of the winner and loser portfolios with more than just one volatility model. Moreover, to examine whether stocks in the winner and loser portfolios tend to become more volatile when they approach the formation date of the momentum portfolio, this study looks at the volatility of stocks in the winner and loser portfolios over the 6 months ending at the formation date and compares it with the volatility over the 6 months preceding it.

Zhang (2006) measures stock volatility by the standard deviation of weekly market excess return. Recall that the major aim of this study is to compare the explanatory power of stock returns volatility and the industry-adjusted stock returns volatility in the cross-sectional variations in stock returns. While Zhang (2006) shows that there are six proxies for information uncertainty that exhibit differential momentum returns, this study aims to assess the interaction between the industry effect and the firm-specific factors on the differential momentum returns. Volatility could be adjusted to industry and thus represents an appropriate variable to examine hypothesis 5. Additionally, volatility exhibits the second largest cross-sectional dispersion in momentum returns after the "age" factor which is measured by the number of years since the firm was first covered by the Center for Research in Securities Prices (CRSP). In order to capture the industry effect, the assumption is that the volatility contains macro components associated with the industry volatility, whereas the industry-adjusted or the idiosyncratic volatility is free of any industry effect. This means that the first measure of volatility should not be adjusted to factors that might comprise components related to industry. To avoid indirectly controlling for the industry effect residing in the market return, it is suggested that stock returns are not adjusted to market returns. This suggestion is put forward to ensure that the industry effect is not isolated from the standard deviation of weekly stock returns if they were adjusted to market returns.

Two models are used to estimate the stocks' volatility to ensure that the estimated volatility of the winner and loser portfolios is not biased by the choice of the volatility measure. The first is the standard deviation (σ) of the stock returns and the second is the Garman–Klass (G–K) price volatility estimator. σ is estimated from the weekly stock returns over the 52 weeks prior to the formation date.

$$\sigma_{i,t} = \sqrt{\frac{\sum_{w=t-51}^{w=t}\left(r_{i,w} - \bar{r}_i\right)}{n-1}} \tag{3.2}$$

where $r_{i,w}$ is the Wednesday-to-Wednesday[40] return of stock i at time t, $\bar{r}_i$ is the stock i weekly average return over the past 52 weeks, and σ_{it} is the stock's standard deviation at time *t* from weekly returns over the period *t-51* to *t*.

In the G–K model, the opening jumps are also controlled for as suggested by Yang and Zhang (2000)[41]. The Garman–Klass model with control to the opening jumps is:

$$\sigma = \sqrt{\frac{Z}{n}\sum\left[\left(\ln\frac{O_w}{C_{w-1}}\right)^2 + \frac{1}{2}\left(\ln\frac{H_w}{L_w}\right)^2 - (2\ln 2 - 1)\left(\ln\frac{C_w}{O_w}\right)^2\right]} \tag{3.3}$$

where *Z* is the number of closing prices in a year, *n* is the number of historical prices used for the volatility estimate, *O* is the opening price, *H* is the high price, *L* is the low

[40] Wednesday weekly prices are used to control for the weekend effect.

[41] Yang and Zhang (2000) derive an extension to the Garman–Klass historical volatility estimator that allows for opening jumps.

price, C is the closing price and w is the Wednesday of the week at which prices are collected. To test for the statistical inference of the estimated volatility of the winner and loser portfolios, this chapter employs a nonparametric test for this purpose, namely the Wilcoxon Rank – Sum test.

As mentioned earlier in this section, since the major aim is to find out whether the industry components within the conventional volatility measure (σ) could explain the cross-sectional variations of momentum returns, the objective of this study is to separate the industry effect, if any, from the estimated volatility and reapply the same methods again. If the estimated industry-adjusted volatility provides similar results to the unadjusted volatility, then momentum profits are not fully explained by industry factors. In this study, two methods are proposed to estimate the adjusted volatility. The first method of adjustment is to regress the past 52 weekly individual stock returns on the industry returns and then to calculate the standard deviation of the residual term which would represent the idiosyncratic volatility. In every month t, the idiosyncratic volatility is estimated for all stocks from the following equation:

$$r_{it} = \alpha_i + \beta_i R_{It} + \varepsilon_{it} \qquad (3.4)$$

where $r_{i,t}$ is the weekly return of stock i at time t, $R_{I,t}$ is the weekly return of the industry sector I (which stock i belongs to) at time t and $\varepsilon_{i,t}$ is the residual term at time t. Therefore, the idiosyncratic volatility will be the standard deviation of the residual term $\varepsilon_{i,t}$.

If stock i's return was not highly correlated to the industry return or happens to lag the industry return then beta β_i might be non–significant. This might have implications on the observed variance of the residual term. Alternatively, it is likely that the degree of volatility of the stock is similar to the degree of volatility of the industry over a certain period even when their weekly returns do not move instantaneously together in the same direction. Hence, the second method of adjustment entails regressing the past 52 weekly stock's σ observations (standard deviation of stock returns) on the past 52 weekly industry's σ observations (standard deviation of industry returns. Thus, there are 52 weekly observations of the dependent and explanatory variables used in the regression, where each observation (σ for each stock and industry) is based on weekly returns over the past 52 weeks. This proposition is based on the argument that companies within the same industry have the same degree of volatility. The adjusted volatility is the sum of squares of the residuals from the following equation:

$$\sigma_{it} = \varphi_i + \theta_i \sigma_{It} + \xi_{it} \qquad (3.5)$$

where σ_{it} is the stock's standard deviation at time t from weekly returns over the period $t\text{-}51$ to t, $\sigma_{I,t}$ is the standard deviation of industry sector I (which stock i belongs to) at time t from weekly returns over the period $t\text{-}51$ to t at time t, and $\xi_{i,t}$ is the residual term at time t. The adjusted volatility is then the sum of squares of the residuals $\xi_{i,t}$.

$$adjusted\ volatility = \sum_{t-51}^{t} (\xi_{it})^2 \qquad (3.6)$$

While in equation 3.4, the dependent and explanatory variables are weekly returns, the standard deviation (square root of the variance) of the residual term $\varepsilon_{i,t}$ (σ) is estimated from the squared deviations of each residual observation from the mean value of the residual term. The standard deviation of $\varepsilon_{i,t}$ represents the volatility of the stock return that is independent of the industry return. However, in equation 3.5, the dependent and explanatory variables each represent the standard deviation of the stock return and the industry sector return, respectively. Since, the purpose of applying equation 3.5 is to measure the part of variation in the stock volatility σ_{it} that does not covary with the industry sector volatility $\sigma_{I,t}$ (explanatory variable), then the sum of squares of the residual term $\xi_{i,t}$ is estimated to represent the variance in σ_{it} that is independent of $\sigma_{I,t}$.

3.5 Results

The proposed hypotheses are tested and the results are displayed and discussed in the following sub-sections. First, this chapter examines the robustness of momentum strategies when portfolios of various liquidity levels are employed. Furthermore, based on the assumption that illiquid stocks are more volatile, the winner and loser portfolios that are formed of liquid stocks are expected to have lower volatility than other samples. Hence, the second sub-section of this chapter tests whether the volatility of the loser and winner portfolios varies as a result of excluding less liquid stocks. After that the chapter investigates the impact of volatility on cross-sectional dispersion in momentum returns and compares the findings to previous studies. Finally, the chapter examines whether that impact, if any, is driven mainly by the industry volatility or whether it is a firm-specific result.

3.5.1 Momentum profits and frequency of trading

Previous work in finance points to the possibility of nonsynchronous trading to drive the autocorrelation in stock returns. However, there has not been any study that examined the variation of momentum profits with respect to various liquidity levels samples. This sub-section, therefore, intends to examine the hypothesis of whether momentum profits would reduce or even disappear as a result of excluding stocks that are not traded every month or week during the 6 months period prior to the formation date[42].

The zero-cost momentum portfolio is formed as previously described in the Data and Methodology section. At each calendar month the stocks are ranked with respect to their performance in the previous j months and held for k months. Table 3.3 exhibits the returns to the winner, loser and winner minus loser portfolios for 3 momentum strategies of $J \times K$ 6x6, 9x3 and 12x3. Each of the 3 momentum strategies is applied to sample 'A' (the same sample from the previous empirical chapter), sample 'B' (that excludes stocks that are not traded at least once every month during the 6 months prior to the formation date) and sample 'C' (that excludes stocks that are not traded at least once every week during the 6 months prior to the formation date) over the sample

[42] Since this study seeks to provide insightful implications to fund managers on the implementation of momentum strategies, excluding stocks that are not traded over a period of time during the holding period is irrelevant to such audience as they can not foresee the trading frequency of the stock in the future (assuming that the formation date is the present date). Even if the results were different when controlling for liquidity during the holding period, the findings will mislead investors as they would never be sure about the stock's future circumstances. Hence, controlling for liquidity during the holding period does not comply with the essence of technical trading of which one type is momentum investment strategies.

period 1987 to 2004. Comparing the results across the 3 samples examines the relevance of momentum profits to various liquidity samples.

The results from table 3.3 show that momentum profits persist across all samples and for all applied strategies. For the 6x6 strategy, it is shown that the monthly average momentum profits are 2.35%, 2.07% and 2.23% (all significant at the 1% level) for samples 'A', 'B' and 'C', respectively. The returns to the loser portfolios are also significant but not for the winner portfolios. Also, momentum profits are shown significant at 1% for the 9x3 and 12x3 strategies across all samples. However, samples 'B' and 'C' reveal striking evidence by generating monthly average momentum profits that are above 2% in all but one case. The notion that nonsynchronous trading partially contributes to momentum profits does not find strong support in these findings. If lead-lag effect, which suggests that larger (and more liquid) stocks lead the smaller stocks, is mainly responsible for momentum profits, then it is expected that – holding the momentum strategy constant – momentum profits should be lower in sample C than in sample B which should in turn be lower than in sample A. However, the findings suggest that a momentum strategy consisted of more liquid stocks that trade weekly generates higher returns than a strategy consisting of monthly traded stocks in the 6x6 and 9x3 strategies. For instance, the 6x6 momentum strategy generates monthly average profits of 2.23% and 2.07% for samples C and B, respectively. The significant and high momentum profits in samples B and C indicate that liquidity is not the driving source of momentum profits; neither does it have a significant role in explaining the short-term continuation of stock returns. The significant returns to the loser portfolios in sample C consisting of highly liquid weekly traded stocks raise concerns about the "short sales constraints" argument which indicates that short sales constraints is a major trading barrier to momentum strategies. While it is expected that such constraints are less severe among highly liquid stocks, the significant negative returns of the loser portfolios of sample C suggest that short sales constraint may not be necessarily responsible for momentum profits, at least for stocks of sample C. This finding provides new evidence to fund managers and market traders on the possibility of exploiting momentum profits from the UK stock market. However, the next empirical chapter discusses this matter in more detail.

Based on previous studies in the literature, it is less likely for large stocks in sample C to be led by other stocks; hence momentum profits, at least, in sample C could be hardly argued to be driven by the lead-lag effect. Lo and Mackinlay (1990a) examine the cross-autocorrelations among sized-based portfolios[43] find that although large stocks lead small stocks, there is no significant evidence of cross-autocorrelation arising from small (or even large) stocks leading other large stocks. This implies that it is less likely to claim that cross-autocorrelations among stocks are the reasons behind the observed momentum profits. The most fitting alternative explanation is that autocorrelations in individual stock returns drive past winners (losers) to continue to gain more (less) over the holding period. In line with the common view among many academics, these findings suggest that momentum returns are the results of short-term positive autocorrelations in stock returns. The short-term positive autocorrelations in stock returns are argued by many as a result of slow market response to new information (Chan et al., 1996; Chan et al., 1999; Barberis et al., 1998; JT, 2001) or due to some investors who are attempting to chase past trends in which case the short-term positive autocorrelations could be looked at as a delayed overreaction rather than underreaction (Daniel et al., 1998).

To clarify this issue further, it is important to look at the return behaviour of the winners and losers at each event month separately. Since the lead-lag effect is less likely to occur within sample C as mentioned above, this chapter investigates whether positive autocorrelations persist beyond the 6 months period and examines whether stocks return reversal occur at an earlier stage than that found in the previous chapter for sample A. In the previous chapter, it is shown that the monthly average momentum profits lessen after event month 11 and reverse after 24 months, but that was tested for what is identified here as Sample A. However, for a sample dominated by highly liquid weekly traded stocks, it is not necessary that the same results are obtained, meaning that the market would require less than 11 months to incorporate delayed news into prices and less than 11 months for the difference between winners and losers to fade away. The monthly event framework is applied to Sample C in order to examine the return behaviour of winners and losers after the holding period. This methodology is also

[43] Size-based portfolios are highly correlated to the liquidity of the stocks as argued and shown by Lo and Mackinlay (1990b) who argue that the stocks of similar market values are likely to have similar nontrading probabilities

applied to tables 7, 8 and 9 of the previous empirical chapter. An early reversal in the winner and loser portfolios' returns indicates that the market is overreacting to information.

Table 3.3

Momentum returns relative to the liquidity of stocks

This table displays the momentum profits in percentage for the strategies 6x6, 9x3 and 12x3 for three samples of various liquidity levels. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous *J*-month performance and held for K months. Stocks that are traded at least once every 3 months, every month, and every week during the formation period constitute Sample A, Sample B, and Sample C, respectively. Stocks in the top decile are assigned to the Winner portfolio, and those in the lowest decile to the Loser portfolio. A zero-cost portfolio is formed by buying Winners and selling Losers. The average monthly returns of the zero-cost portfolios are held after skipping a month after the formation date. The Newey-West Heteroskedasticity and Autocoorrelation-consistent *t*-statistics are reported in parentheses. The sample period is 1987 – 2005.

JxK	**Low traded Sample** **Sample A**	**Monthly traded Sample** **Sample B**	**Weekly traded Sample** **Sample C**
6x6			
W	0.43 (0.96)	0.31 (0.73)	0.16 (0.34)
L	-1.92 (-2.80)†	-1.76 (-2.60)†	-2.07 (-2.70)†
W – L	**2.35** **(5.01)**†	**2.07** **(4.55)**†	**2.23** **(3.81)**†
9x3			
W	0.57 (1.24)	0.39 (0.83)	0.42 (0.85)
L	-2.13 (-2.99)†	-1.69 (-2.51)*	-1.71 (-2.24)*
W – L	**2.70** **(4.83)**†	**2.08** **(3.88)**†	**2.13** **(3.25)**†
12x3			
W	0.68 (1.38)	0.70 (1.50)	0.45 (0.87)
L	-1.91 (-2.69)†	-1.87 (-2.59)†	-1.52 (-2.03)*
W – L	**2.59** **(4.28)**†	**2.57** **(4.20)**†	**1.97** **(2.89)**†

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

For each month within the sample period, the stocks are ranked according to past return performance and their 12 months holding period returns are determined after skipping a month between formation periods and holding periods. This methodology – event time – averages the returns of first event month across all formed portfolios. The same method is repeated for second event month and so on up to 12th event month.

Since there are 216 portfolios formed between January 1987 and December 2004, then there are 216 observations for event month 1, event month 2 holding period, etc. The average of these observations is estimated to explain the return behaviour of the momentum portfolio in each holding month separately.

Table 3.4 shows insignificant returns for winners in the weekly traded sample for all strategies and during each event month. Moreover, although negative returns dominate the behaviour of winner portfolios during the 12 months holding period, there is not a significant early reversion in returns to imply evidence of past-trend chasing. On the other hand, the loser portfolios returns are larger in magnitude for all strategies. For the 6 months ranking period, loser returns are significantly negative in 8 out of the 12 event months. As the ranking period j increases, the number of significant negative returns months decreases. For instance, there are six (three) significant negative returns for the loser portfolios when the ranking period is 9 (12) months. This also holds true for the significance of the momentum profits, as it appears that there are less holding period months with significant profits for strategies with longer ranking periods. The findings here again indicate that the cycle of the momentum is shortened at the holding period side when the ranking period increases from 6 to 12 months. Moreover, the losers seem to be driving the largest part of momentum profits. One possible explanation for the observed returns is the disposition effect. The fact that winners change their sign but losers remain negative for almost 12 months after formation date indicates a tendency towards realising gains from winning stocks and reluctance to realise losses from losers as put by Shefrin and Statman (1985). Since the employed sample consists of only stocks traded at least once every week, the continuation of the losers' negative returns but not of the winners' returns could be attributed to the tendency to hold losers long in the hope of short term mean reversion where today's losers are expected to outperform today's winners (See Andreassen, 1988 and Odean, 1998).

Table 3.4

Momentum Returns using the event time study

This table reports momentum returns in an event time method. At each month within the sample period, all stocks within the Sample C (weekly traded stocks) are ranked based on their past *j* months returns. Stocks in the top decile are assigned to the Winner decile, and those in the lowest decile to the Loser decile. The average monthly returns of the Winner, Loser and "Winners – Losers" portfolios for 12 event months are presented, skipping a month between formation and holding period. The Newey-West Heteroskedasticity and Autocoorrelation-consistent *t*-statistics are reported in parentheses. The sample period is 1987 – 2005.

Holding Period		**J = 6**			**J = 9**			**J = 12**	
	Winners	**Losers**	**W – L**	**Winners**	**Losers**	**W – L**	**Winners**	**Losers**	**W – L**
1	0.51% (1.00)	-2.52% (-2.78)†	3.03% (3.77)†	0.67% (1.32)	-1.91% (-2.26)*	2.58% (3.60)†	0.77% (1.47)	-2.17%(-2.60)†	2.94% (3.95)†
2	0.07% (0.16)	-2.21% (-2.69)†	2.29% (3.16)†	0.16% (0.34)	-1.71% (-2.23)*	1.87% (2.72)†	0.27% (0.55)	-1.33% (-1.79)^	1.60% (2.34)*
3	0.17% (0.03)	-2.13% (-2.77)†	2.30% (3.51)†	0.29% (0.57)	-1.61% (-2.19)*	1.90% (2.77)†	0.14% (0.28)	-1.16% (-1.59)	1.30% (1.78)^
4	-0.12% (-0.23)	-2.21% (-2.84)†	2.09% (3.29)†	2x10^{-3}% (0.00)	-1.66% (-2.30)*	1.67% (2.60)†	-0.47% (-0.84)	-1.50% (-1.98)*	1.02% (1.31)
5	0.12% (0.25)	-2.02% (-2.68)†	2.14% (3.62)†	0.02% (0.04)	-1.24% (-1.70)^	1.26% (1.88)^	-0.31% (-0.55)	-1.21% (-1.60)	0.89% (1.15)
6	-0.08% (-0.16)	-1.63% (-2.19)*	1.55% (2.56)*	-0.16% (-0.29)	-1.25% (-1.71)^	1.09% (1.54)	-0.47% (-0.79)	-0.97% (-1.40)	0.50% (0.68)
7	-0.22% (-0.43)	-0.98% (-1.56)	0.76% (1.43)	-0.24 % (-0.45)	-0.72% (-0.96)	0.48% (0.66)	-0.52% (-0.87)	-0.56% (-0.77)	0.04% (0.05)
8	-0.04% (-0.06)	-1.11% (-1.68)^	1.07% (1.68)^	-0.51% (-0.87)	-0.85% (-1.14)	0.34% (0.45)	-0.72% (-1.09)	-0.67% (-0.90)	-0.05% (-0.06)
9	-0.25% (-0.43)	-1.24% (-1.76)^	0.99% (1.55)	-0.45% (-0.82)	-0.65% (-0.98)	0.20% (0.29)	-0.56% (-0.87)	-0.67% (-1.02)	0.11% (0.15)
10	-0.37% (-0.69)	-0.78% (-1.18)	0.41% (0.66)	-0.41% (-0.68)	-0.80% (-1.27)	0.39% (0.60)	-0.56% (-0.92)	-0.82% (-1.25)	0.26% (0.36)
11	-0.29% (-0.56)	-1.10% (-1.64)	0.81% (1.30)	-0.78% (-1.40)	-0.52% (-0.87)	-0.26% (-0.40)	-0.51% (-0.89)	-0.24% (-0.39)	-0.27% (-0.40)
12	-0.51% (-1.05)	-0.37% (-0.59)	-0.14% (-0.25)	-0.35% (-0.65)	-0.64% (-1.06)	0.29% (0.48)	-0.48% (-0.95)	-0.15% (-0.24)	-0.33% (-0.56)

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

In summary, this sub-section has shown that momentum strategies could generate high profits even when based on very liquid stocks, and that these profits seem to be driven largely by losers. Although momentum profits are significantly positive, an analysis of the winner and loser portfolios confirms earlier findings in the previous chapter that losers contribute more to momentum profits than winners even among highly liquid stocks. Highly liquid stocks have shorter profitable momentum life; nonsynchronous trading is not a primary factor yet there exist other factors that are driving momentum profits that should be addressed.

3.5.2 Volatility of the Winner and Loser portfolios

In the previous sub-section, it is shown that samples of highly liquid stocks generate momentum profits and hence the momentum phenomenon could not be attributed to thinly traded stocks. This subsection estimates the volatility of the winner, loser and momentum portfolios to test whether the higher contribution to momentum profits arising from losing stocks relates to a higher volatility. In other words, this subsection examines the possibility that the difference in the degree of volatility between winners and losers justifies the variations in the magnitude of winner and loser portfolios returns. The Wilcoxon Rank – Sum test is employed to test for the significance of the observed volatility values and the significance of their difference.

For each of the 3 liquidity samples predefined earlier, volatility is estimated for the winner, loser and momentum portfolios. This study applies two historical volatility measures, the conventional sigma σ (standard deviation) and the Garman-Klass model that are both based on historical stock returns. Furthermore, since this chapter uses both decile and quintile formations, the volatility is estimated for the winner (loser) portfolios when they represent both the top (bottom) deciles and quintiles of all stocks ranked upon their past performance. At each month during the sample period, all stocks within samples A, B and C are ranked upon their past 6 months returns. The volatility of the winner (loser) portfolio is the equally weighted average volatility of all stocks in that portfolio, whereas W-L denotes the difference between the estimated volatilities of the winner and loser portfolios.

Table 3.5 presents the estimated volatility of the winner, loser and momentum portfolios measured by the standard deviation of stock returns over the past 26 weeks where the returns are derived from weekly prices[44]. As shown below in table 3.5, the volatility of the loser portfolio is larger than that of the winners across all samples and for both the decile classification as well as for the quintile classification. For instance, in sample A, the winner decile standard deviation (hereafter s.d.) is 4.48% and that of the loser decile is 6.53% representing on average 69 firms in each decile. The difference of 0.018 is maintained across the other two samples. In fact, the loser decile s.d. exceeds that of the winner in 181 cases of the total 216 within sample A while similar findings are found for both samples B and C.

In addition to the standard deviation of weekly returns, this study employs a weekly range estimator of volatility to see whether the volatility characteristics of the winner and loser portfolios are sensitive to the volatility measure used. The G–K model confirms the results of the standard deviation measure that losers experience higher volatility than winners during the formation period. The volatility of the loser deciles exceeds that of the winners by more than 1.8% in samples A and B and by 0.68% in sample C. The difference between the observed volatilities for winners and losers is reduced when using the quintile procedure, yet it remains significant for all samples. The Z-statistics values of the Wilcoxon Rank – Sum test are displayed in table 3.5 with the p-values. For all the observed differences between the volatilities of the winner and loser portfolios, the results are significant at 1%. Therefore, based on the observed results, the null hypothesis H_0 *: volatility of the winners = volatility of the losers* is rejected. The higher volatility of the losers compared to the winners could be argued to be responsible for the larger (in absolute value) returns and hence draw implications that being riskier, losers tend to be driving the largest part of momentum profits.

[44] Estimating σ from the past 26 or the past 52 weekly returns essentially provide similar implications about the volatility of the winner, loser and momentum portfolios. However, table 3.6 below shows that the volatility of the loser stocks tend to increase substantially towards the formation date. To avoid sorting the stocks in the next subsection – about volatility and cross-sectional dispersion in momentum returns – with respect to a temporarily increased volatility, this study suffices to stick with volatilities estimated on past 52 weeks in the next sub-section which is in compliance with the study of Zhang (2006).

The σ and the G–K model exhibit similar results. Firstly, the volatility of the losers is significantly larger than that of the winners for all samples and under both tests. Secondly, the reported volatility estimates between both tests are quite close and comparable. For instance, the σ of the winners and losers are 4.45% and 6.54% for sample B using the decile classification. The same portfolios have G–K estimates of 4.44% and 6.20%. Therefore, for the interest of brevity, in the next sub-section, the study employs the σ measure only which is also unsophisticated to adjust for industry.

The evidence provided here is in line with the evidence from Ang et al. (2006) who show that stocks with higher volatility tend to earn lower average returns. Similarly, the loser portfolios – that earns the least – have a higher volatility level than the winners. But since stocks within winners and losers tend to revert in the long run according to the long term reversal of stock returns behaviour, and as some losing stocks might even make it to the top performing portfolio, then the volatility of individual stocks should vary in a way that keeps the loser portfolio always more volatile i.e. stocks should experience higher volatility when they tend to earn less. To investigate this issue further of whether volatility builds up over time and gets higher when the stock tends to be earning lower returns, this study examines the variation in stock returns volatility over a period of 12 months before it approaches the formation date.

This matter is investigated by comparing the volatility of the losers (winners) during the past 6 months before formation date with the losers' (winners') volatility in the 6 months preceding that period. A period of 6 months for each period is not chosen arbitrarily. Recall that the ranking period for the momentum strategy employed here is 6 months, which implies that winners (losers) have on average 6 months of good (bad) performance. However, a stock that is in the winner (loser) decile or quintile does not necessitate that it is earning the most (least) close to the formation date, i.e. a stock could still fall in the winner portfolio yet it earns negative returns in the month before the formation date. Therefore, and to avoid such potential problems, the 12 months period before the formation date is split into two periods and volatility within each is compared.

Table 3.5

Volatility (measured by the sigma and Garman-Klass model) for all samples relative to liquidity

This table reports the median volatility of the Winner (W) and Loser (L) portfolios and their difference (W – L) in three samples of various liquidity levels. Each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous 6 months performance. Stocks that are traded at least once every 3 months, every month, and every week during the formation period constitute Sample A, Sample B, and Sample C, respectively. Stocks in the top decile (or quintile) are assigned to the Winner portfolio, and those in the lowest decile (or quintile) to the Loser portfolio. The zero-cost investment portfolio is the winner minus loser portfolio. The volatility of the Winner (Loser) portfolio is the equally weighted average volatility of all stocks in the Winner (Loser) portfolio over the 26 weeks before the formation date. σ is the square root of the variance estimated using weekly returns from Wednesday to Wednesday. The Garman-Klass model is estimated from weekly prices and adjusted for opening jumps according to Yang-Zhang (2000). Weekly data used to estimate the volatility measures span over the period 1986 – 2004. The *Z*-statistics of the Wilcoxon Rank test are reported with the corresponding p-values in parentheses.

		Sigma σ						**Garman-Klass**					
		Deciles			Quintiles			Deciles			Quintiles		
		W	L	W – L	W	L	W – L	W	L	W – L	W	L	W – L
Sample A	Median	**0.0448**	**0.0653**	**-0.0196**	**0.0407**	**0.0521**	**-0.0132**	**0.0441**	**0.0621**	**-0.0182**	**0.0395**	**0.0508**	**-0.0114**
	Wilcoxon Rank Test	1.86	2.45	10.28	1.19	2.92	9.83	1.95	2.42	9.79	2.02	2.75	9.52
	(P-Value)	(0.061)	(0.014)	(0.000)	(0.232)	(0.003)	(0.000)	(0.050)	(0.015)	(0.000)	(0.042)	(0.005)	(0.000)
Sample B	Median	**0.0445**	**0.0654**	**-0.0227**	**0.0400**	**0.0531**	**-0.0143**	**0.0444**	**0.0620**	**-0.0187**	**0.0394**	**0.0508**	**-0.0118**
	Wilcoxon Rank Test	1.95	3.09	10.35	2.17	3.26	10.11	1.35	2.47	9.82	2.07	2.81	9.64
	(P-Value)	(0.051)	(0.002)	(0.000)	(0.029)	(0.001)	(0.000)	(0.175)	(0.013)	(0.000)	(0.037)	(0.004)	(0.000)
Sample C	Median	**0.0458**	**0.0659**	**-0.0196**	**0.0417**	**0.0536**	**-0.0123**	**0.0457**	**0.0520**	**-0.0068**	**0.0405**	**0.0463**	**-0.0050**
	Wilcoxon Rank Test	2.21	2.20	8.51	2.21	2.59	8.46	1.29	2.69	5.59	2.68	2.49	5.93
	(P-Value)	(0.027)	(0.027)	(0.000)	(0.026)	(0.009)	(0.000)	(0.195)	(0.006)	(0.000)	(0.007)	(0.012)	(0.000)

Table 3.6 presents the results for the variation in volatility of the winner and loser portfolios over time. The standard deviation is estimated for each stock over the 6 months preceding the formation date is designated as $\sigma_{t-6,\,t}$ and the σ over the 6 months preceding the formation period is designated $\sigma_{t-12,\,t-6}$. The difference between the two estimated volatilities is the variation in stock volatility between the formation period and the period preceding it and is designated by $\Delta\sigma|_t = \sigma_{t-6,t} - \sigma_{t-12,t-6}$. Initially, the variation in volatility is estimated for each stock within the winner and loser portfolios. Then, the variation in stock volatility $\Delta\sigma|_t$ for the winner (loser) portfolio is the average of variation in volatility for all stocks within the winner (loser) portfolios at time *t*. The results show that the loser portfolios tend to become riskier as they approach the formation date regardless of the liquidity level of the sample. One would argue that this could be attributed to the loser stocks becoming less liquid as investors holding them refrain from selling them at a loss and hold them until their prices rise back. But since this is happening to all stocks including those in sample C, then it can not be simply attributed to liquidity. This matter is, however, beyond the scope of this study and is therefore left for future research. Nonetheless, the same is not true for the winner portfolios as they tend to become less volatile towards the formation period, yet the decrease in volatility is not significant for all samples. For the decile strategy, the losers' volatility increases by 1.44%, 1.57% and 1.65% for samples A, B and C, respectively. On the other side, the decrease in the volatility of the winner portfolios is only significant for sample A where it is -0.19% (at 10% level of significance).

Since returns of the winner and loser portfolios reverse over long periods as shown in the monthly event study of the previous chapter that examines sample A, then the allocation of stocks into the loser portfolios definitely changes over time. This implies that when stocks perform badly they experience periods of higher volatility, but that volatility varies and should decrease when these stocks perform better. These findings are compatible with those of Ang et al. (2006) who find that stocks with higher volatility earn on average lower returns than low volatility stocks, in that the changing allocation of winners and losers is met with a varying σ. As shown in table 3.4, the 6x6 strategy does not deliver any significant returns for winners; this evidence and the negative reported $\Delta\sigma|_t$ are in compliance with the results of Ang et al. (2006). However, it should be clarified that if Stock X is generally more volatile than Stock Y, then this does not necessarily mean that Stock X should be earning less than Stock Y. The implication from this study suggests that stocks are riskier when they are performing badly and the aggregate volatility of the worst performing stocks is higher than the aggregate volatility of the good performers. De Bondt and Thaler (1987) find for a different strategy with opposite positions (short in winners and long in losers) that losers have lower (higher) risk in Down (Up) markets.

In conclusion, this sub-section shows that the loser portfolios are significantly more volatile than the winner portfolios for all levels of liquidity which verifies the riskiness and larger contribution of loser portfolios to momentum profits. Employing σ and historical price estimator of volatility essentially provide similar findings with respect to the winner and loser portfolios. The volatility of the loser portfolio tends to increase as it approaches the formation date of the momentum portfolio which suggests that estimating the volatility of a loser stock over a short period before formation might bias the results.

Table 3.6

Variation of Volatility over time for all samples relative to liquidity

This table reports the median variation in volatility of the Winner (W) and Loser (L) portfolios and their difference (W – L) in three samples of various liquidity levels. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous 6 months performance. Stocks that are traded at least once every 3 months, every month, and every week during the formation period constitute Sample A, Sample B, and Sample C, respectively. Stocks in the top decile (quintile) are assigned to the Winner portfolio, and those in the lowest decile (quintile) to the Loser portfolio. σ is the square root of the variance estimated using weekly returns from Wednesday to Wednesday. The difference in the value of the standard deviation (σ) of the stock's return over the two periods (the first spanning over the 26 weeks ending at the formation date and the second spanning over the 26 weeks before the first period) is estimated for each stock. The variation in volatility for all stocks within any portfolio is equally weighted for month t. Weekly data used to estimate the volatility measures span over the sample period is 1986 – 2004. t-statistics are reported in parentheses.

$$\Delta\sigma|_t = \sigma_{t-6,t} - \sigma_{t-12,t-6}$$

	Decile			Quintile		
	W	L	W – L	W	L	W – L
Sample A	-0.0019 (-1.77)^	0.0144 (11.68)†	-0.0164 (-13.61)†	-0.0025 (-2.84)†	0.0082 (7.93)†	-0.0107 (-12.92)†
Sample B	-0.0012 (-1.13)	0.0157 (12.69)†	-0.0169 (-14.51)†	-0.0018 (-2.01)*	0.0092 (8.90)†	-0.0111 (-13.80)†
Sample C	-0.0001 (-0.10)	0.0165 (11.04)†	-0.0167 (-11.35)†	-0.0007 (-0.77)	0.0094 (7.83)†	-0.0102 (-10.74)†

The superscripts †, *, ^ denote statistical significance at 1%, 5%, and 10% respectively.

3.5.3 Momentum profits and stock volatility

In view that momentum profits exist among various liquidity level samples, this study continues to examine the impact of the stock volatility on momentum returns over various liquidity level samples; this is based on the assumption that differential momentum returns due to volatility should not be associated with illiquid stocks as evidence in the previous subsections show that varying the level of liquidity does not eliminate momentum profits. The volatility is an appropriate variable to examine the variation in momentum returns as previous evidence by Zhang (2006) and Ang et al. (2006) show that stock return volatility – as a proxy for information uncertainty – affects the future returns and hence the profitability of the momentum strategy and, moreover, stock volatility is associated with industry volatility which allows an investigation of the role of industry in the cross-section of momentum returns. This subsection deals with the former issue and the next subsection examines the latter one.

Having shown in the previous subsection that losers are more volatile than winners and that losers' volatility increases as the formation date approaches, and together with the findings that losers contribute to momentum profits more than winners do, this subsection examines whether the higher volatility implies larger (in absolute value) returns. To put it in a different way, if past performance is held constant, would the more volatile stocks generate larger (in absolute value) returns?

Zhang (2006) argues that stocks with higher volatility (as a proxy for information uncertainty) underreact to news more than stocks with lower volatility, and hence, winners with higher volatility gain more than winners with lower volatility, whereas losers with higher volatility generate lower returns than lower volatility losers[45]. Alternatively, the findings of Ang et al. (2006) indicate that stocks with higher volatility earn less than stocks with lower volatility despite their past performance. This subsection aims to clarify the ambiguity regarding the relation of stock volatility and momentum returns by providing evidence from an alternative and major stock market.

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[45] While high volatility losers generate lower returns than low volatility loser, their higher negative return on the short side of the momentum strategy implies higher positive returns.

The implemented methodology entails that stocks are ranked on their past 6 months performance and divided into quintiles, with the top quintile containing the best past performers (past winners). Afterwards, stocks within each quintile are ranked on the basis of their volatility[46], estimated from the s.d. of the past 52 weekly returns prior to the formation date, and sorted into 3 equal sub-portfolios, with the top sub-portfolio within each quintile containing stocks of high volatility. The double sorting method results in 15 sub-portfolios. The last column exhibits the cross-sectional dispersion in momentum returns with respect to volatility for each momentum quintile; whereas the bottom row exhibits the momentum returns after controlling for volatility for each volatility tercile. The stock volatility in this section is the total volatility of the stock return without adjusting for systematic risk. Table 3.7 exhibits the results for the double sorting methodology. The portfolios are formed with accordance to the past 6 months returns and are held for 1 month to provide comparable results to Zhang (2006) and Ang et al. (2006); Furthermore, to ensure that the impact of volatility on the cross-section of momentum returns is not influenced by the short-term overreaction which might affect the returns of highly volatile stocks more than less volatile ones, a robustness check is performed by examining a longer holding period of 6 months; i.e. testing the impact of volatility with respect to the 6x6 conventional strategy.

Table 3.7 displays the monthly average returns for all samples. Panel 'A' reports the results for sample A which are analysed and discussed at first. For the 1 month holding period, the results show that the sub-portfolio returns increase as volatility declines regardless of past performance. The "High– Low" column shows the difference in the returns between the high volatility and low volatility sub-portfolios after controlling for the momentum effect. The low volatility sub-portfolios significantly outperform the high volatility sub-portfolios for all momentum quintiles. Similar findings are obtained for the 6 months holding period strategy; in fact, low volatility sub-portfolios outperform high volatility ones significantly for the 6x1 and 6x6 strategies. These findings are supportive of those of Ang et al. (2006) and contradict the

[46] Stock volatility is measured as the standard deviation of the stock's returns over the past 12 months. The previous subsection reveals that using another historical price estimate of volatility (Garman–Klass) produces the same implications about the volatility of the winner and loser portfolios, and hence it is sufficient to employ the standard deviation estimate which is in line with other studies investigating the same matter.

assumption that higher volatility implies higher underreaction and hence larger absolute value returns over the holding period. In particular, for the 6x6 strategy, the differential "High– Low" return within the winner quintile is -0.74% (at 1% level of significance) which implies that even over an extended holding period (6 months) lower volatility winners outperform high volatility ones, where the latter, according to Zhang (2006), is supposed to be experiencing higher underreaction and earning higher returns. Low volatility winners generate a monthly average of 0.60% and 0.75% (at 10% and 5% level of significance, respectively) for 1 and 6 months holding periods, respectively. While low volatility stocks earn significant returns when extending the holding period, this is not the case for the returns of high volatility winners which are very low and insignificant for both holding periods. The dispersion in the cross-sectional momentum returns is wider for the loser quintile, where it is -2.54% and -1.89% for the 6x1 and 6x6 strategies, respectively. The differential "High – Low" return is negatively correlated to the quintile past return for the 6x1 strategy, while for the 6x6 strategy, the difference reduces then increases when moving from the past winner to the past loser quintile.

On the other hand, the "W – L" row indicates the dispersion in the returns between winners and losers, where winners and losers belong to high, medium or low volatility portfolios. The cross-sectional difference between winners and losers is greatest for the high volatility stocks and declines monotonically with volatility. For instance, under the 6 months holding period, the "W – L" portfolio generates 2.49%, 1.60% and 1.34% monthly average returns for high, medium and low volatility terciles, respectively. This means that a momentum strategy based on high volatility stocks generates almost twice the returns of that based on low volatility stocks. The outperformance of the high volatility momentum strategy is due to the riskiness of the high volatility losers. However, a superior momentum strategy from the double sorting methodology would be holding a long position in low-volatility-past-winners and a short position in high-volatility-past losers which generates a 3.76% (*t–statistics* 5.33) monthly average return for the 6x1 (not presented in table 3.7). To wrap up, although a momentum strategy based on high volatility stocks is more profitable than one based on low volatility stocks, this is mainly attributed to the loser portfolios since the "High– Low" is only -0.49% for the winner quintile compared to -2.54% for the loser quintile for 6x1 strategy.

Yet, before final conclusions are drawn from the results of sample A, both samples B and C are tested over the same methodology and their results are reported in panels 'B' and 'C', respectively. All together, the three panels of table 3.7 provide evidence on the dispersion of momentum returns with respect to volatility in interaction with the level of liquidity of the stocks. This allows us to see whether the impact of volatility is more effective on some stocks rather than others.

Looking at the variation in returns by controlling for the momentum effect, panels 'B' and 'C' show that, for all momentum quintiles in both strategies, the dispersion in the cross-sectional momentum returns is significant, which confirms earlier findings from sample A. The volatility effect on the cross-section of momentum returns does not disappear with higher liquidity stocks since the significance of the "High – Low" return persists among both samples B and C for all momentum quintiles. In particular, the differential "High – Low" return increases (in absolute value) from sample A to sample B[47] but then from sample B to sample C the results are mixed. For instance, in the 6x1 (6x6) strategy, the magnitude of the "High – Low" return increases from 0.49% to 0.62% to 0.72% (0.74% to 0.86% to 0.95%) for the winner quintiles in samples A, B and C. The magnitude of the "High – Low" return for the loser quintile of the 6x6 strategy increases from 1.89% to 1.97% to 2.30% among samples A, B and C, respectively. In general, the volatility effect on the cross-section of momentum returns in sample B dominates that of sample A. However, weekly traded stocks within sample C present mixed results as their middle quintiles seem to be less vulnerable to the volatility cross-sectional effect than the extreme winner and loser quintiles. Thus, the volatility effect is present in the cross-section of momentum returns even at the more liquid stocks and, hence, is not subject to illiquid stocks.

Controlling for the volatility level of the individual stocks, momentum profits increase with volatility for samples B and C similar to sample A. High volatility stocks generate larger momentum profits than low volatility stocks, regardless of the liquidity level of the individual stocks. However, while the losers drive the momentum profits for the high volatility tercile, the winners drive the momentum profits of the low volatility

[47] Except for the middle quintile of the 6x1 strategy, the "High – Low" return magnitude of sample B is larger than that of sample A.

tercile for all samples. The "W – L" return of the 6x1 strategy for the high volatility stocks is 3.27%, 3.38% and 3.23% for samples A, B and C, respectively. Also, for the low volatility stocks, the "W – L" return of the 6x1 strategy increases from 1.22% (sample A) to 1.42% (sample B) but then decreases to 0.96% (sample C). The larger momentum profits of the higher volatility stocks also hold for the 6x6 strategy. The conclusion from these results is that momentum strategies are most profitable among high volatility stocks. The "W – L" returns in panels 'A', 'B' and 'C' are all significant at either 1% or 5%.

Overall, the results from examining the cross-sectional effect of volatility on momentum returns are robust among various levels of liquidity samples. Larger momentum profits obtained by high volatility stocks should not be interpreted as a consequence of small illiquid stocks that are usually expensive to trade as they tend to persist with the weekly traded stocks. One potential explanation is that investors demand a higher expected return from losers, therefore increasing its risk; when these firms fail to meet the expectations of the loser holders, their prices will further fall, leading to a downward trend as that observed in the losers' return. Moreover, the difference in returns between a 6x1 momentum strategy that is based on high volatility and one that is based on low volatility is 2.05% for sample A and 2.27% for sample C which indicates the stronger presence of the volatility effect in the more frequently traded stocks.

Table 3.7

Portfolio returns by Momentum and Stock Volatility

This table shows the impact of stock volatility on the cross-section of momentum returns. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous 6 months performance and held for 1 month or 6 months. Stocks that are traded at least once every 3 months, every month, and every week during the formation period constitute Sample 'A', Sample 'B', and Sample 'C', respectively. Stocks in the top quintile are assigned to the Winner portfolio, and those in the lowest quintile to the Loser portfolio. Within each quintile stocks are equally sorted into 3 subportfolios on the basis of the volatility of the individual security. Stock volatility is measured from the standard deviation σ of the stock's 52 past weekly returns prior to the formation date. The monthly average returns of the sub-portfolios for all quintiles are presented in percentages when they are held a month after the formation date. The Newey-West *t*-statistics are reported in parentheses. The sample period is 1987 – 2005.

Panel A: Sample A

	1 month holding period				6 months holding period			
	High Volatility	Medium Volatility	Low Volatility	High – Low	High Volatility	Medium Volatility	Low Volatility	High – Low
Winners	0.11	0.44	0.60	**-0.49**	0.01	0.50	0.75	**-0.74**
	(0.22)	(1.19)	(1.65)^	**(-1.85)^**	(0.02)	(1.54)	(2.49)*	**(-2.93)†**
Quintile 2	-0.15	0.30	0.45	**-0.60**	-0.11	0.49	0.63	**-0.74**
	(-0.33)	(0.87)	(1.41)	**(-2.57)***	(-0.25)	(1.59)	(2.24)*	**(-3.67)†**
Quintile 3	-0.44	0.16	0.37	**-0.81**	-0.19	0.28	0.52	**-0.71**
	(-1.03)	(0.47)	(1.16)	**(-4.96)†**	(-0.44)	(0.90)	(1.76)^	**(-4.31)†**
Quintile 4	-0.85	-0.05	0.16	**-1.01**	-0.66	0.04	0.20	**-0.86**
	(-1.64)	(-0.13)	(0.45)	**(-3.71)†**	(-1.29)	(0.13)	(0.59)	**(-3.63)†**
Losers	-3.16	-1.36	-0.62	**-2.54**	-2.48	-1.10	-0.59	**-1.89**
	(-3.73)†	(-2.45)*	(-1.22)	**(-5.19)†**	(-3.09)†	(-1.95)^	(-1.24)	**(-3.96)†**
W – L	**3.27**	**1.80**	**1.22**	2.05	**2.49**	**1.60**	**1.34**	**1.15**
	(4.92)†	**(4.40)†**	**(3.18)†**	(4.36)†	**(4.63)†**	**(4.22)†**	**(4.63)†**	**(2.81)†**

	1 month holding period				6 months holding period			
	High Volatility	Medium Volatility	Low Volatility	High – Low	High Volatility	Medium Volatility	Low Volatility	High – Low
Panel B: Sample B								
Winners	0.08	0.53	0.70	**-0.62**	-0.03	0.52	0.83	**-0.86**
	(0.06)	(1.47)	(1.91)^	**(-2.14)***	(-0.11)	(1.63)	(2.74)†	**(-3.22)†**
Quintile 2	-0.31	0.34	0.47	**-0.78**	-0.11	0.51	0.72	**-0.83**
	(-0.60)	(0.82)	(1.47)	**(-3.13)†**	(-0.25)	(1.59)	(2.40)*	**(-3.91)†**
Quintile 3	-0.51	0.17	0.60	**-1.11**	-0.21	0.27	0.59	**-0.80**
	(-1.13)	(0.45)	(1.70)^	**(-6.53)†**	(-0.50)	(0.80)	(1.89)^	**(-4.75)†**
Quintile 4	-0.98	-0.09	0.01	**-0.99**	-0.73	-0.03	0.21	**-0.94**
	(-1.82)^	(-0.21)	(0.06)	**(-3.77)†**	(-1.37)	(-0.06)	(0.57)	**(-3.94)†**
Losers	-3.30	-1.24	-0.72	**-2.58**	-2.56	-1.02	-0.59	**-1.97**
	(-3.74)†	(-2.20)*	(-1.35)	**(-5.10)†**	(-3.12)†	(-1.82)^	(-1.17)	**(-4.09)†**
W – L	**3.38**	**1.77**	**1.42**	1.96	**2.53**	**1.54**	**1.42**	1.11
	(4.87)†	**(4.10)†**	**(3.77)†**	(4.08)†	**(4.61)†**	**(3.97)†**	**(4.70)†**	(2.79)†
Panel C: Sample C								
Winners	-0.06	0.41	0.66	**-0.72**	-0.22	0.39	0.73	**-0.95**
	(0.00)	(0.94)	(1.73)^	**(-2.02)***	(-0.32)	(1.13)	(2.14)*	**(-2.57)***
Quintile 2	-0.43	0.50	0.66	**-1.09**	-0.10	0.55	0.65	**-0.75**
	(-0.82)	(1.47)	(1.68)^	**(-3.58)†**	(-0.22)	(1.71)^	(2.25)*	**(-3.04)†**
Quintile 3	-0.18	0.12	0.48	**-0.66**	-0.12	0.58	0.56	**-0.68**
	(-0.36)	(0.20)	(1.13)	**(-2.21)***	(-0.26)	(1.76)^	(1.71)^	**(-3.00)†**
Quintile 4	-0.57	-0.12	0.23	**-0.80**	-0.62	-0.03	0.56	**-1.18**
	(-1.02)	(-0.29)	(0.99)	**(-2.07)***	(-1.10)	(-0.11)	(1.69)^	**(-3.75)†**
Losers	-3.29	-1.59	-0.30	**-2.99**	-2.68	-1.10	-0.38	**-2.30**
	(-3.17)†	(-2.53)*	(-0.84)	**(-3.72)†**	(-2.99)†	(-1.81)^	(-1.03)	**(-3.57)†**
W – L	**3.23**	**2.00**	**0.96**	2.27	**2.46**	**1.49**	**1.11**	1.35
	(3.50)†	**(3.53)†**	**(2.25)***	(2.72)†	**(3.84)†**	**(2.93)†**	**(2.91)†**	(2.39)*

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

3.5.4 Momentum returns and idiosyncratic volatility

So far, the chapter has presented evidence that of a significant effect of total volatility on the cross-section of momentum returns in the London Stock Exchange. However, a number of studies have associated the stock volatility to common factors such as market and industry (See Campbell et al. 2001; and Black et al. 2002). Since the level of liquidity is not found to be driving the volatility effect in momentum returns, two objectives are addressed in this subsection following the outcome from the previous subsection: the first is to examine whether the power of volatility in explaining the cross-sectional dispersion in momentum returns is due to the industry effect or firm-specific factors, and the second is to examine the extent of the industry role in explaining the cross-sectional variations in momentum returns relevant to the level of liquidity[48]. To control for the industry effect, the idiosyncratic volatility is obtained from regressing the stock's return on its industry's return[49] as shown in equation 3.4 in the methodology section. Therefore, the s.d. of the residual term ($\varepsilon_{i,t}$) from equation 3.4 replaces the stock volatility in the previous subsection. The regression is applied at each formation month within the sample period i.e. for each month between January 1987 and December 2004, inclusive. For each stock within the tested sample, the 52 weekly stock return observations ending at the formation week of the portfolio are regressed against the weekly industry sector returns of the same period. The double sorting methodology is applied as in the previous subsection by ranking stocks firstly on their past 6 months performance and sorting them into quintiles and secondly by sorting the stocks within each quintile into 3 sub-portfolios based on the estimated s.d. of the residual term ($\varepsilon_{i,t}$) obtained from the above regression.

The results of the above methodology are presented in table 3.8 for holding periods of 1 month and 6 months. Panels 'A', 'B' and 'C' of table 3.8 report the results for samples A, B and C, respectively. The findings from table 3.8 indicate that using the

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[48] The second objective is based on the assumption that market wide news are reflected in large and liquid stocks in advance of smaller and less liquid stocks and, hence, the industry role should have a larger immediate impact on the former group of stocks and a lesser and slower effect on the latter group.

[49] Other studies define the idiosyncratic volatility as the residual from the FF-3 factor model. However, the emphasis here is to explore the role of industry in explaining the variation in momentum returns relative to high and low volatility stocks.

idiosyncratic volatility rather than the total volatility (as in table 3.7) has certainly some differences which are discussed in terms of the industry effect on each sample employed. Starting with sample A, the "High – Low" portfolios yield negative significant returns for all quintiles after controlling for the momentum effect where stocks of high idiosyncratic volatility underperform those of low idiosyncratic volatility similar to the results of the previous subsection. In comparison with the previous subsection, table 3.8 panel 'A' shows that the dispersion in momentum returns relative to idiosyncratic volatility is generally larger than that of the total volatility especially for the top two quintiles. This means that high idiosyncratic volatility stocks continue to earn lower future returns than low idiosyncratic volatility stocks after controlling for the momentum effect. These results again support the findings of Ang et al. (2006) who use the standard deviation of the residual term from the FF-3 factor model to represent the idiosyncratic volatility of a stock and find lower future returns for higher idiosyncratic volatility stocks. Since "High – Low" return remains significant when the idiosyncratic volatility is used, then the industry effect can not explain the observed cross-sectional dispersion, at least for sample A. The preliminary conclusion from these findings suggests that the cross-sectional dispersion in stock returns with respect to volatility is a firm-specific feature not an industry feature in the first place.

As well as obtaining similar findings in the "High – Low" portfolios, the return dispersions among the "W – L" portfolios are larger for the high idiosyncratic volatility than for the low idiosyncratic volatility portfolios similar to the results of the total volatility in the previous subsection. Thus, a momentum strategy based on stocks of high idiosyncratic volatility remains more profitable than one based on stocks of low idiosyncratic volatility. For instance, the return to the "W – L" portfolio of sample A in the 6x6 strategy declines from 2.49% to 1.60% to 1.39% (all significant at the 1% level) as idiosyncratic volatility progressively decreases. The results obtained are very close to those of the total volatility where the "W – L" portfolio earns 2.49%, 1.60% and 1.34% as volatility declines.

Despite the similarities in the main findings, that the "W – L" and the "High – Low" portfolios continue to observe significant returns, there are some distinctions after adjusting for industry for the more liquid samples B and C. The return magnitude of the "High – Low" portfolios of samples B and C is larger among the winner portfolios and smaller among the loser portfolios when idiosyncratic volatility is used than when total volatility is used. In other words, when idiosyncratic volatility replaces total volatility, the differential return between the high volatility winners (losers) and the low volatility winners (losers) becomes larger (smaller). That change in the value of the "High – Low" return is economically small for both winners and losers. For example, looking at the 6x6 strategy in panel 'B' (of tables 3.7 and 3.8), the losers' "High – Low" return is –1.97% and declines to –1.90% after using an idiosyncratic volatility. For sample C, the observed drop in the "High – Low" return magnitude declines from 2.30% using total volatility to 2.18% using idiosyncratic volatility. This drop in the monthly average return dispersion relative to the idiosyncratic volatility could be attributed to the larger extent of the role of the industry effect in samples B and C rather than sample A. This is probably because the returns of more frequently traded stocks reflect their industry news faster than the less liquid stocks of sample A, so when employing an idiosyncratic volatility, the dispersion in returns due to the industry effect is captured by the weekly and monthly traded stocks, though this effect cannot explain the return dispersion. However, the idiosyncratic volatility has an opposite effect on the "High – Low" return for the winner portfolios where the "High – Low" return tends to increase suggesting that the dispersion in the winners' returns between high and low volatility stocks is related to idiosyncratic components whereas that in the losers' returns is partially due the industry effect. This is evident in the reported results in panel 'C' of both tables 3.7 and 3.8, where the winners' "High – Low" return magnitude increases (in absolute value) from 0.95% to 1.11% in the 6x6 strategy and from 0.72% to 0.91% in the 6x1 strategy when total and idiosyncratic volatility are used, respectively.

Moving on to the returns of the "W – L" portfolios within samples B and C, there is another remarkable finding after adjusting volatility to the industry effect. There is a tendency for momentum profits (W – L) to decrease among high volatile stocks after adjusting for the industry component in the volatility. A 6x6 momentum strategy that is based on high total volatility stocks (table 3.7) earns a monthly average of 2.53% and 2.46% (both at 1% level of significance) for samples B and C, respectively; however, the same strategy earns 2.44% and 2.25% (both at 1% level of significance) when based on high idiosyncratic volatility stocks for the same samples, respectively. Thus, the industry effect partially explains the large momentum profits of the high volatility stocks. However, the partial and small role of industry is most obvious among high volatility portfolio of the weekly traded stocks in that it reduces its monthly average momentum profits by 0.21% (2.46% – 2.25%). The monthly average momentum profits of the low total volatility weekly traded stocks is 1.11% and becomes 1.18% after using idiosyncratic volatility in the 6x6 strategy. While industry seems to play a partial role in explaining the cross-sectional momentum returns of highly liquid stocks, the firm-specific component of the stock volatility appears to explain the cross-sectional momentum returns of the less liquid stocks.

The findings in this subsection support earlier studies that show evidence of industry momentum strategies such as Moskowitz and Grinblatt (1999) and Swinkels (2002), but in particular the findings of panel 'C' confirm the implications of Scowcroft and Sefton (2005) that while industry momentum drive momentum profits of large-cap stocks, firm-specific components influence momentum profits at the small-cap level. While their approach is different from that in this chapter, the implication that the industry role is present at frequently traded and highly liquid stocks is analogous to both studies.

Furthermore, it is shown that under the idiosyncratic volatility sorting, the high volatility stocks in the loser portfolios earn more than those under the total volatility sorting (for samples B and C), whereas in the winner portfolios they appear to earn lower returns under the idiosyncratic volatility sorting. This implies that when redistributing the stocks within each quintile and sorting them into 3 sub-portfolios according to the idiosyncratic volatility[50], some of the extreme bad performing stocks become allocated in either the medium volatility or low volatility sub-portfolio in the loser quintile, however, the opposite happens among the winner quintile where the high volatility sub-portfolio earn lower returns. Hence, the past performance of certain stocks within the winner quintile is attributed to their specific component, while a fraction of the past performance of certain stocks in the loser quintile is attributed to the industry effect.

[50] Note that for any momentum quintile, the average return of the 3 sub-portfolios within that quintile is equal among tables 3.7 and 3.8. For instance, the monthly average return of the winner quintile of sample C in the 6x6 strategy is 0.89% and 0.90% in tables 3.7 and 3.8, respectively. The slight observed differences (in this example it is 0.0001) that might occur are due to estimation faults such as rounding the last digit.

Table 3.8

Portfolio returns by Momentum and stock idiosyncratic volatility

This table shows the impact of stock volatility on the cross-section of momentum returns. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous 6 months performance and held for 1 month or 6 months. Stocks that are traded at least once every 3 months, every month, and every week during the formation period constitute Sample 'A', Sample 'B', and Sample 'C', respectively. Stocks in the top quintile are assigned to the Winner portfolio, and those in the lowest quintile to the Loser portfolio. Within each quintile stocks are equally sorted into 3 sub-portfolios on the basis of the volatility of the individual security. Stock volatility is the standard deviation σ of the past 52 weekly observations of the residual term from the regression $r_{i,t} = \alpha_i + \beta_j R_{I,t} + \varepsilon_{i,t}$, where $r_{i,t}$ is stock *i*'s weekly return at time t, $R_{I,t}$ is the weekly return of the industry sector of which stock I belongs to at time t and $\varepsilon_{i,t}$ is the residual term at time t. The average monthly returns of the sub-portfolios for all quintiles are presented when they are held a month after the formation date. The Newey-West *t*-statistics are reported in parentheses. The sample period is 1987 – 2005.

Panel A: Sample A

	1 month holding period				6 months holding period			
	High Volatility	Medium Volatility	Low Volatility	High – Low	High Volatility	Medium Volatility	Low Volatility	High – Low
Winners	0.11	0.38	0.65	**-0.54**	-0.01	0.50	0.79	**-0.80**
	(0.24)	(0.98)	(1.82)^	**(-2.06)***	(-0.01)	(1.51)	(2.59)^	**(-3.19)†**
Quintile 2	-0.18	0.30	0.46	**-0.64**	-0.15	0.50	0.64	**-0.79**
	(-0.41)	(0.88)	(1.41)	**(-2.74)†**	(-0.35)	(1.57)	(2.21)*	**(-3.95)†**
Quintile 3	-0.47	0.15	0.37	**-0.84**	-0.22	0.27	0.51	**-0.73**
	(-1.09)	(0.46)	(1.12)	**(-4.98)†**	(-0.50)	(0.83)	(1.71)^	**(-4.41)†**
Quintile 4	-0.87	-0.04	0.15	**-1.02**	-0.69	0.02	0.20	**-0.89**
	(-1.65)^	(-0.10)	(0.41)	**(-3.78)†**	(-1.34)	(0.06)	(0.60)	**(-3.78)†**
Losers	-3.20	-1.35	-0.64	**-2.56**	-2.50	-1.10	-0.60	**-1.90**
	(-3.80)†	(-2.35)*	(-1.28)	**(-5.29)†**	(-3.13)†	(-1.93)^	(-1.26)	**(-4.06)†**
W – L	**3.31**	**1.73**	**1.29**	2.02	**2.49**	**1.60**	**1.39**	1.10
	(5.17)†	**(3.90)†**	**(3.59)†**	(4.46)†	**(4.69)†**	**(4.15)†**	**(4.93)†**	(2.76)†

	1 month holding period				6 months holding period			
	High Volatility	Medium Volatility	Low Volatility	High – Low	High Volatility	Medium Volatility	Low Volatility	High – Low
Panel B: Sample B								
Winners	0.03	0.52	0.75	**-0.72**	-0.07	0.53	0.86	**-0.93**
	(0.67)	(1.38)	(2.09)*	**(-2.66)†**	(-0.14)	(1.58)	(2.82)*	**(-3.34)†**
Quintile 2	-0.27	0.26	0.52	**-0.79**	-0.11	0.52	0.72	**-0.83**
	(-0.60)	(0.68)	(1.62)	**(-3.48)†**	(-0.28)	(1.61)	(2.42)*	**(-4.27)†**
Quintile 3	-0.51	0.19	0.57	**-1.08**	-0.18	0.25	0.58	**-0.76**
	(-1.17)	(0.53)	(1.69)^	**(-6.33)†**	(-0.43)	(0.78)	(1.83)^	**(-4.62)†**
Quintile 4	-0.97	-0.08	-0.002	**-0.96**	-0.69	-0.05	0.21	**-0.90**
	(-1.79)^	-(0.22)	(-0.00)	**(-3.74)†**	(-1.36)	(-0.14)	(0.56)	**(-3.93)†**
Losers	-3.20	-1.31	-0.75	**-2.45**	-2.51	-1.06	-0.61	**-1.90**
	(-3.70)†	(-2.27)*	(-1.44)	**(-5.17)†**	(-3.08)†	(-1.82)^	(-1.26)	**(-4.08)†**
W – L	**3.23**	**1.83**	**1.50**	**1.73**	**2.44**	**1.59**	**1.47**	**0.97**
	(5.04)†	**(3.99)†**	**(4.22)†**	**(4.16)†**	**(4.55)†**	**(3.96)†**	**(5.07)†**	**(2.52)***
Panel C: Sample C								
Winners	-0.17	0.43	0.74	**-0.91**	-0.34	0.47	0.77	**-1.11**
	(-0.33)	(0.98)	(2.04)*	**(-2.67)†**	(-0.64)	(1.18)	(2.48)*	**(3.29)†**
Quintile 2	-0.38	0.44	0.68	**-1.06**	-0.12	0.57	0.65	**-0.78**
	(-0.77)	(1.16)	(1.79)^	**(-3.58)†**	(-0.28)	(1.78)^	(2.23)*	**(-3.24)†**
Quintile 3	-0.24	0.13	0.53	**-0.77**	-0.07	0.53	0.57	**-0.65**
	(-0.49)	(0.35)	(1.56)	**(-2.65)†**	(-0.16)	(1.60)	(1.82)^	**(-2.98)†**
Quintile 4	-0.61	0.006	0.25	**-0.86**	-0.52	-0.05	0.55	**-1.07**
	(-0.89)	(0.01)	(0.69)	**(-2.46)***	(-0.97)	(-0.12)	(1.60)	**(-3.78)†**
Losers	-3.30	-1.56	-0.33	**-2.97**	-2.59	-1.15	-0.41	**-2.18**
	(-3.14)†	(-2.30)*	(-0.68)	**(-3.71)†**	(-2.86)†	(-1.74)^	(-0.82)	**(-3.52)†**
W – L	**3.13**	**1.99**	**1.07**	**2.05**	**2.25**	**1.62**	**1.18**	**1.07**
	(3.40)†	**(3.39)†**	**(2.59)***	**(2.47)***	**(3.54)†**	**(3.12)†**	**(3.21)†**	**(1.96)^**

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

Investigating the effects of both industry and liquidity on the cross-section of momentum returns clarifies more issues about the incentives of momentum profits and provides further evidence to the literature. This subsection shows that idiosyncratic volatility adjusted to industry returns does not explain the cross-section dispersion in momentum returns with respect to volatility; however, it does have a partial role among the highly liquid stocks. The industry effect seems to slightly influence the returns of the losing stocks; yet, the impact is too small to explain the return behaviour of the loser portfolios.

3.5.5 Momentum returns and adjusted sigma

Since only stocks within sample C trade on a weekly basis during the formation period, then one can assume that many stocks may experience nonsynchronous trading especially within sample A. Assuming that some stocks trade only once every month, then their weekly observed zero returns would be less correlated to their industry weekly returns in equation 3.4 and hence the model might not properly control for the industry effect in the stock returns. Although this matter primarily concerns the thinly traded stocks, it also has implications for the frequently traded stocks that are less sensitive to their industry news. Thus a robustness check is needed to provide an alternative approach of separating the industry volatility from the firm-specific component of the stock volatility.

Recall that using the σ_ε from industry-adjusted returns in the previous subsection reveals some aspects of the role of industry in the dispersion of momentum returns, but only among samples B and C. If the stock volatility is associated with its industry and contains components of the industry volatility (Campbell et al., 2001) and if volatility is responsible for the dispersion in momentum returns, then adjusting σ to that of the relevant industry could overcome the limitations in the previous model (equation 3.4) as each σ is estimated from the past 52 weekly stock returns and hence each observation of the dependent variable – based on a whole year of weekly returns – reflects more of its industry volatility on the right side of equation 3.5.

This chapter proposes a new model for adjusting the stock's σ to the industry effect by regressing the σ of the stock on the relative weekly σ of its particular industry. The proposed model employed in this subsection is to estimate the σ-adjusted volatility. The purpose of applying this model is discussed in the methodology subsection 3.4.2.3. To run the above regression, 52 observations of the dependent and the explanatory variables are used. The strategy follows the same procedure as that in the previous subsection except that in the second stage of sorting stocks within each quintile, the stocks are sorted into 3 sub-portfolios according to the estimated sum of squares of the residual term $\xi_{j,t}$.

Table 3.9 exhibits the results of the double sorting methodology using adjusted σ. The results for samples A, B and C are displayed in panels 'A', 'B' and 'C', respectively. The results on the left of panel 'A' for a 1 month holding period show that the dispersion in returns between high and low volatility stocks within the winner quintile is 0.005% (with a t-value: 0.03) i.e. once σ has been adjusted for the industry σ, volatility no longer explains variation in momentum returns among the winners over a holding period of 1 month. Comparing with the results in tables 3.7 and 3.8 where "High – Low" return is –0.49% (at 10% level of significance) and –0.54% (at 5% level of significance), respectively, implies that the variation in the firm-specific volatility is not responsible for the dispersion in returns between high and low volatility stocks for the winner portfolio. Compared with other studies, Zhang (2006), who uses market excess returns to estimate σ, finds that the "High – Low" return of the winner portfolio generates a monthly average of 0.53% (t-value of 1.01) and Ang et al. (2006) find that "High – Low" winner portfolio generates a monthly average of –0.48% (t-value: 2.01) using idiosyncratic volatility which is comparable to the –0.49% (t-value: 1.85) using total volatility and also to the –0.54% (t-value: 2.02) using the idiosyncratic volatility, in table 3.7 and 3.8, respectively. The similarities between the results in tables 3.7 and 3.8 for the winner portfolio and the aforementioned two studies question whether employing the methodology of table 3.9 (adjusting σ to industry) would wither the dispersion in returns between the high and low volatility winners for the US sample.

Another distinguished finding from the previous two tables is that none of the adjusted σ winner sub-portfolios have significant returns over the 1 month holding period. The adjusted σ appears to have an impact on the dispersion in returns among winning stocks but not among losing stocks. For both the 1 and 6 months holding period, the "High – Low" returns for the top two quintiles are obviously reduced when the industry effect is controlled by regressing the σ than when using the idiosyncratic volatility or the total volatility, suggesting that the σ-adjusted volatility can totally or partially explain the dispersion in momentum returns in the top two winning quintiles. As for the loser portfolio, the results do not differ from table 3.8 i.e. high volatility stocks have large significant negative returns whereas low volatility stocks have insignificant negative returns. In the loser quintile the "High – Low" return decreases in comparison with the previous volatility measures used; however, the dispersion between the returns of high adjusted σ and low adjusted σ sub-portfolios remains significant. This suggests that the continuation of high volatility losers to underperform the low volatility losers is mainly attributed to firm-specific components.

Moving on to the momentum profits of portfolios with different volatility levels, the "W – L" momentum profits of the low adjusted volatility portfolios seem to decrease whereas those of the high adjusted volatility increases. Consequently, the differential return between a momentum strategy based on high volatility and one on low volatility increases and reaches 2.36% (at 1% level of significance) for the 6x1 strategy, compared to 2.05% and 2.02% for the same sample and strategy using total volatility and idiosyncratic volatility, respectively.

Next, the impact of the adjusted volatility on the cross-section of momentum returns is discussed for higher liquidity stocks of samples B and C. The first notable finding is that the "High – Low" return decreases for all momentum quintiles in both samples B and C compared to the "High – Low" returns based on total and idiosyncratic volatility. For instance, table 3.9 panel 'B' shows that the "High – Low" return for the winner and loser quintiles in the 6x1 strategy is –0.21% (t-value of 0.98) and –2.15% (at the 1% level of significance) which is substantially different from –0.62% and –2.58% using total volatility and –0.72% and –2.45% using idiosyncratic volatility. The smaller magnitude of the "High – Low" return is more evident in the weekly traded stocks where it reaches half the magnitude of that in table 3.7 for the second quintile of the 6x1 strategy (–0.55% using adjusted σ versus –1.09% using total volatility and –1.06% using idiosyncratic volatility). The second notable finding is that the cross-sectional dispersion in momentum returns among the winner quintile of sample C disappears totally under the 6x1 and 6x6 strategies with the adjusted σ. Furthermore, none of the winner sub-portfolios earn significant returns when stocks are sorted according to the adjusted σ. The "High – Low" return maintains its large magnitude for samples B and C among the loser portfolio although it is smaller than that in the previous two tables. This implies that the role of industry volatility becomes more robust among the highly liquid stocks in that it reduces the cross-sectional dispersion in momentum returns substantially, but further eliminates this phenomenon for the winner portfolio.

Controlling for the level of volatility, high adjusted σ tercile earns larger momentum profits and low adjusted σ tercile earns lower momentum profits than in the previous two tables for sample C. For sample B, the industry effect reduces the momentum profits of the low adjusted σ tercile than in the previous two tables; however, the momentum profits of the high adjusted σ terciles are not considerably different from those in table 3.8 using idiosyncratic volatility.

The robustness check undertaken by regressing the stock's σ on that of its industry sector reveals some of the explanatory capabilities of industry on momentum strategies. There is no disparity in the returns of the winner sub-portfolios when sorted with respect to the adjusted σ; however, the "High – Low" differential returns of the other quintiles are reduced but not eliminated. In addition, it should be highlighted that the industry effect on the cross-section of winner returns increases with the liquidity level of stocks. As industry fails to fully eliminate the cross-sectional return dispersion of all momentum quintiles, then the main factor responsible for it is the firm-specific component of the stock volatility. Specifically for the loser quintiles, where the effect of industry is enhanced using the adjusted σ measure, the differential momentum returns are attributed in the first place to the firm-specific factors.

Table 3.9

Portfolio returns by Momentum and adjusted sigma

This table shows the impact of stock volatility on the cross-section of momentum returns. At each month within the sample period, all stocks within the FTSE All Share are ranked based on their previous 6 months performance and held for 1 month or 6 months. Stocks that are traded at least once every 3 months, every month, and every week during the formation period constitute Sample 'A', Sample 'B', and Sample 'C', respectively. Stocks in the top quintile are assigned to the Winner portfolio, and those in the lowest quintile to the Loser portfolio. Within each quintile stocks are equally sorted into 3 sub-portfolios on the basis of the industry-adjusted volatility of each individual security. The industry-adjusted volatility of each stock is estimated by regressing the last 52 standard deviations $\sigma_{i,t}$ of the stock return against the standard deviations σ_I of the relevant industry: $\sigma_{it} = \varphi_i + \theta_i \sigma_{It} + \xi_{it}$, where $\sigma_{i,t}$ and $\sigma_{I,t}$ are the standard deviations of stock i and its industry sector, respectively, estimated from the past 52 weekly returns prior to week t, and $\xi_{j,t}$ is the residual term at week t. The monthly average returns of the sub-portfolios of all quintiles are presented when they are held a month after the formation date. The Newey-West t-statistics are reported in parentheses. The sample period is 1987 – 2005.

Panel A: Sample A

	1 month holding period				6 months holding period			
	High Volatility	Medium Volatility	Low Volatility	High – Low	High Volatility	Medium Volatility	Low Volatility	High – Low
Winners	0.45	0.27	0.45	**-0.005**	0.25	0.43	0.59	**-0.33**
	(1.11)	(0.65)	(1.31)	**(-0.03)**	(0.66)	(1.22)	(1.89)^	**(-2.19)***
Quintile 2	-0.11	0.26	0.38	**-0.49**	0.02	0.38	0.56	**-0.53**
	(-0.28)	(0.72)	(1.16)	**(-3.18)†**	(0.07)	(1.13)	(1.88)^	**(-3.76)†**
Quintile 3	-0.5	0.2	0.38	**-0.88**	-0.21	0.3	0.49	**-0.70**
	(-1.27)	(0.58)	(1.09)	**(-5.05)†**	(-0.56)	(0.87)	(1.58)	**(-5.21)†**
Quintile 4	-0.65	-0.25	0.11	**-0.77**	-0.6	-0.07	0.22	**-0.83**
	(-1.41)	(-0.6)	(0.32)	**(-4.07)†**	(-1.29)	(-0.19)	(0.64)	**(-5.05)†**
Losers	-3.00	-1.42	-0.63	**-2.37**	-2.27	-1.24	-0.60	**-1.67**
	(-3.87)†	(-2.36)*	(-1.23)	**(-5.79)†**	(-3.27)†	(-2.1)*	(-1.21)	**(-5.62)†**
W – L	**3.45**	**1.69**	**1.09**	**2.36**	**2.53**	**1.67**	**1.19**	**1.34**
	(5.60)†	**(3.76)†**	**(3.09)†**	**(5.54)†**	**(5.42)†**	**(4.46)†**	**(3.97)†**	**(4.86)†**

	1 month holding period				6 months holding period			
	High Volatility	Medium Volatility	Low Volatility	High – Low	High Volatility	Medium Volatility	Low Volatility	High – Low
Panel B: Sample B								
Winners	0.42 (0.95)	0.27 (0.66)	0.63 (1.79)^	**-0.21** **(-0.98)**	0.25 (0.58)	0.43 (1.20)	0.64 (2.00)*	**-0.39** **(-2.16)***
Quintile 2	-0.13 (-0.30)	0.23 (0.60)	0.40 (1.24)	**-0.53** **(-2.81)†**	0.14 (0.36)	0.38 (1.11)	0.60 (1.98)*	**-0.46** **(-3.16)†**
Quintile 3	-0.44 (-1.09)	0.30 (0.81)	0.39 (1.11)	**-0.83** **(-4.63)†**	-0.17 (-0.42)	0.32 (0.90)	0.50 (1.56)	**-0.67** **(-4.58)†**
Quintile 4	-0.78 (-1.61)	-0.31 (-0.70)	0.04 (0.09)	**-0.82** **(-3.66)†**	-0.63 (-1.33)	-0.12 (-0.29)	0.21 (0.56)	**-0.84** **(-5.19)†**
Losers	-2.86 (-3.71)†	-1.66 (-2.51)*	-0.71 (-1.33)	**-2.15** **(-5.39)†**	-2.21 (-3.03)†	-1.37 (-2.24)*	-0.58 (-1.15)	**-1.63** **(-5.14)†**
W – L	**3.28** **(5.43)†**	**1.93** **(3.84)†**	**1.34** **(3.63)†**	**1.94** **(4.84)†**	**2.46** **(5.02)†**	**1.80** **(4.56)†**	**1.22** **(3.93)†**	**1.24** **(4.53)†**
Panel C: Sample C								
Winners	0.36 (0.71)	0.24 (0.55)	0.41 (1.08)	**-0.05** **(-0.17)**	0.21 (0.43)	0.37 (0.95)	0.32 (0.90)	**-0.11** **(-0.41)**
Quintile 2	-0.10 (-0.21)	0.39 (0.95)	0.45 (1.19)	**-0.55** **(-1.99)***	0.17 (0.42)	0.36 (1.07)	0.60 (1.93)^	**-0.43** **(-2.16)***
Quintile 3	-0.11 (-0.25)	0.10 (0.26)	0.39 (1.08)	**-0.50** **(-1.82)^**	0.10 (0.25)	0.40 (1.18)	0.53 (1.65)^	**-0.43** **(-2.08)***
Quintile 4	-0.50 (-1.06)	0.02 (0.04)	0.10 (0.23)	**-0.60** **(-2.01)***	-0.36 (-0.75)	-0.04 (-0.10)	0.37 (1.04)	**-0.73** **(-3.38)†**
Losers	-3.27 (-3.23)†	-1.43 (-2.19)*	-0.51 (-0.89)	**-2.76** **(-3.80)†**	-2.49 (-2.92)†	-1.19 (-1.81)^	-0.46 (-0.89)	**-2.03** **(-4.06)†**
W – L	**3.63** **(4.05)†**	**1.67** **(2.83)†**	**0.92** **(2.02)***	**2.71** **(3.49)†**	**2.70** **(4.24)†**	**1.56** **(3.23)†**	**0.78** **(2.20)***	**1.92** **(3.90)†**

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

3.6 Conclusion

In light of the recent findings in the literature, this chapter investigates the sources for the cross-sectional dispersion in momentum returns relative to volatility. The individual stock volatility contains industry components as well as firm-specific components in addition to other market-wide components. On the other hand, the literature shows that industry momentum strategies are as profitable as individual stocks momentum strategies and that industry plays a significant role in momentum returns. Therefore, this chapter examines the impact of industry-adjusted volatility on the cross-section of momentum returns to investigate whether the cross-sectional variation in momentum returns is due to industry or idiosyncratic volatility. However, since the market-wide information – hence, industry news – is more present in large liquid stocks, this chapter examines the proposed hypotheses among 3 various liquidity level samples to see whether the industry effect varies with respect to the level of liquidity.

Momentum profits persist among the 3 employed liquidity samples: the original sample from the previous chapter; a sample of stocks that are traded at least once every month; and a sample of stocks that are traded at least once every week during the past 6 months. Therefore momentum profits are not associated with trading obstacles that prevent investors from exploiting the unrealised profits as the sample of weekly traded stocks occur to earn a monthly average return of 2.23% in a 6x6 momentum strategy.

Since the literature shows inconsistencies regarding the momentum performance of high volatility stocks with respect to low volatility stocks, this chapter looks at the volatility of the momentum portfolios at various levels of liquidity to examine whether the highly illiquid stocks are causing such ambiguity in the literature. The findings in this chapter are that the volatility of the winner and loser portfolios is not considerably different among the 3 liquidity samples. However, in each liquidity sample, the volatility of the losers is significantly higher than that of the winners. In an attempt to investigate the issue further, loser portfolios tend to become more volatile as they approach the formation date, whereas the opposite result is found for the winner portfolios.

Furthermore, this chapter examines the impact of volatility on momentum returns, i.e. the impact of total volatility of stock returns after controlling for the momentum effect. The results are in line with the findings of Ang et al. (2006) that low volatility stocks earn higher returns than high volatility stocks for all momentum quintiles. The suggestion that higher volatility implies higher underreaction and hence larger return magnitudes does not find support in the results of this study as suggested by Zhang (2006). Momentum strategies of high volatile stocks outperform those of low volatile stocks; however, it should be noted that while losers drive the momentum profits of high volatile portfolios, the winners' contribution to momentum profits rise at the low volatile portfolios.

To adjust for the industry effect, stock returns are regressed on the respective industry sector returns, and the standard deviation of the residual term is used to replace the total volatility. As a result of employing the idiosyncratic volatility, the cross-sectional dispersion in momentum returns reduces slightly on the losers' side, but unexpectedly, the idiosyncratic volatility accentuates the dispersion at the winners' side for the liquid stocks.

A robustness test on adjusting for the industry effect entails that the stock's σ is regressed against its industry's σ and the sum of squares of the residual term replaces the total volatility. The newly proposed model of adjustment manages to explain the differential cross-sectional momentum returns of the winner portfolios but only reduces it partially for the loser portfolios. The impact of the adjusted σ increases with liquidity which supports the suggestion that market-wide information is incorporated more in the highly liquid stocks than in low liquidity level samples. Since all momentum quintiles, except the winners, maintain their significant differential return between high and low volatility stocks after adjusting σ, then it is argued that the primary cause of that dispersion in the cross-section of momentum returns is due to firm-specific attributes or other common microstructure effects.

This chapter concludes that the role of industry in the cross-section of momentum returns relative to volatility is limited to the highly liquid stocks and is in line with Scowcroft and Sefton (2005) who argue that the industry effect has more presence at the large-cap stocks whereas firm-specific components influence profits at the small-cap level. Industry volatility could explain the dispersion at the winners' side (and partially at the losers' side). The overall evidence suggests that industry can play a small role in momentum even when the framework of a study is based on individual stocks; however, its restricted role in the loser portfolios even for the weekly traded stocks raises questions of whether firm-specific components or other market microstructure effects such as short sales constraints could be responsible for the persistence of significant returns in these stocks. Liquidity is a principal factor that should be taken into account when evaluating the impact of market-wide versus firm-specific components on the cross-section of momentum returns.

4 Chapter Four: Trading Costs, Underreaction and Momentum Profits

4.1 Introduction

In the previous empirical chapter, it has been shown that losers are more volatile than winners and that their volatility tends to increase as they approach the formation date. While the industry effect fails to explain the cross-sectional effect of volatility on the losers' returns, this chapter intends to investigate issues related to the potential sources for the observed continuing returns of the loser portfolios. Also building on the previous empirical chapter, where momentum profits were shown to persist among highly liquid weekly traded stocks, this chapter aims to explore whether momentum profits could reside not only in highly liquid stocks but among those stocks that suffer the least from information ambiguity and price inefficiencies.

In an efficient market, assuming costless trading, prices should reflect information instantaneously and expected future abnormal returns should not be different from zero. Hence, speculation on the current publicly available information fails to generate excess returns and, as a result, momentum profits would not exist. Assuming a real market framework, momentum profits must not exceed trading costs in order for the efficient market hypothesis to hold. Since trading frequency and the level of trading costs vary among stocks then incorporation of information into prices should subsequently vary as well. Testing the momentum effect in a sample of stocks with a relatively high speed of price adjustment to news would provide evidence of whether the concept of market efficiency applies to stocks with more precise and instant information.

Earlier in chapter 2 it was shown that arbitrageurs have not been able to fully eliminate the cross-sectional disparity in returns between past good and poor performers for years after the discovery of momentum profitability, despite evidence that such profits are fading for strategies that hold positions beyond 6 months in the more recent time window (post-2000). As a result, researchers as well as investors have increasingly become interested to find out whether these were real market profits. Accordingly, there is a growing volume of literature which links the persistence of momentum profits to trading barriers such as transaction costs and short-selling constraints. These studies suggest that transaction costs and short sales constraints impede traders from updating their positions to benefit from any mispricing and eliminate the realised returns (see, for example, Lesmond et al., 2004; Korajczyk and Sadka, 2004; Ali and Trombley, 2006). Their findings imply that after adding the costs for trading and the constraints to short-selling into the whole picture, it would not be possible to earn any profit from the relative strength or momentum strategies.

The larger contribution to momentum profits is shown to be generated by past losers (Hong et al., 2000; JT, 2001; Lesmond et at., 2004). This fact is also shown in the previous empirical chapters where past poor performers realise larger absolute returns and lengthy continuing returns compared to past good performers, which confirms the higher contribution from the losers' side. Earning from the past poor performers is, however, constrained by the availability and costs of short-selling. This raises concerns of whether the persistence of momentum profits could be largely attributed to the high transaction costs and short sales constraints associated with past poor performers.

Since it has also been shown in the previous chapter that the returns to the past losers are significantly negative over a 6 months testing period among a sample of weekly traded stocks, then slow price adjustments could not be solely attributed to trading obstacles such as transaction costs since these stocks are traded at least once every week. Instead, slow price adjustments could be due to the market underreaction to information such as underreaction to earnings announcements[49]. However, revealing precise news about the value of the stock should consequently minimise the underreaction phenomenon.

Thus, two issues are addressed which require deeper investigation into their relevance to momentum returns: trading costs and short sales constraints on the one hand, and slow price adjustment due to information asymmetry, noise and ambiguity on the other hand. Alternatively, trading in options provides investors with financial tools

[49] This is argued to generate momentum profits according to Chan et al. (1996) and which is referred to, in Barberis et al. (1998), as a behavioural bias, namely conservatism.

that facilitate speculative trading[50]. Especially, stock options allow investors to substitute the short-selling procedure by holding positions in the options market. Trading in the options market, in turn, "*should lead to short sales by options market makers and cause an increase in short interest that is associated with options trading*" (Figlewski and Webb, 1993). Further to their impact on mitigating short sales constraints, it is argued that options improve the informational efficiency of the underlying securities. The evidence from trading in the options market has shown that stock prices adjust faster and information asymmetry among traders is reduced (see, for example, Cao, 1999; Damodaran and Lim, 1991; Huang and Wang, 1997; Jennings and Starks, 1986; Skinner, 1990). Hence, the increase in informational efficiency and the lower costs, especially on the losers' side, due to option trading should reduce or eliminate momentum profits among the underlying stocks where investors have an alternative leveraged approach to exploit their information specifically with respect to past poor performing stocks.

The motivation of this study stems from earlier findings in the literature concerning the increase in the speed of price adjustment after option listing, and the higher level of liquidity and price changes[51] caused by option trading. Optioned stocks should have less uncertainty regarding the value of the firm, and their lower transaction costs should facilitate the elimination of abnormal returns. In this context, the argued speed of price adjustment for stocks with listed options increases the informational efficiency of the underlying stocks and the lower transaction costs do not prevent informed investors from trading on their signals. Subsequently, this study intends to investigate the impact of listed options on the momentum profits of the underlying stocks to draw implications on whether faster price adjustments to news and lower trading costs could partially reduce or even eliminate momentum profits.

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[50] Black and Scholes (1973) argue that option contracts are redundant to the price of the underlying assets if markets were complete, competitive and frictionless. However, given the trading barriers such as transaction costs and short sales constraints, options might affect the price of the underlying assets.
[51] See Conrad (1989) and Easley et al. (1998) for evidence on price increase following option trading

The profitability of momentum strategies for samples with listed options is compared with that of holdout samples of non-optioned stocks[52]. This aims to examine whether option listing could provide a substitute for short-selling and eliminate or reduce the momentum profits in the market. The samples of non-optioned stocks, or the control samples, are constructed with relevance to the market value, turnover and percentage spreads of the stocks to represent a reliable comparison. This is done to control for factors (such as market value, turnover and percentage spreads) that characterise the stock return behaviour and to avoid biases arising from comparisons with small, illiquid or more costly to trade stocks. Size, volume and bid-ask spreads form a reliable benchmark for examining a sample of optioned stocks versus a control sample of non-optioned stocks. One further control sample is constructed using a logit model which determines the stocks that are the nearest neighbours to those with listed options. The nearest neighbours are selected on the basis of the three factors put together.

This chapter also focuses on the profitability of momentum strategies in the UK market after adjusting to trading costs. Some studies suggest that the cost to trade on the LSE is relatively high, which leaves many stocks non-traded over long periods in the LSE. Momentum returns are adjusted to the quoted spread trading cost estimate – that is based on the bid and ask prices during the formation period – to provide a reliable comparison with the US studies. A new trading cost model is presented in this study based on quoted prices at the execution dates of the formation and liquidation of the portfolio. The purpose of the newly proposed estimate is to capture the effect of the changing bid–ask spread width over the momentum cycle that current trading cost estimates overlook. Trading costs adjusted momentum profits for the UK market provide an out of sample test. It is therefore crucial to examine whether such transaction costs vary among the different employed samples.

[52] Given that our sample period starts from the 1990, it is not possible to test the effect before and after option listing because there are few stocks that were optioned after that date which are not sufficient to test such a hypothesis despite its importance.

4.2 Literature Review

This section reviews in detail the literature in relation to the issues raised above. There is extensive literature on the impact of options on the various aspects of the underlying stocks. This section reviews the finance literature on listed options and their effect on price efficiency, liquidity, transaction costs and short sales constraints. After a comprehensive analysis of the effects of option listing and option trading, assumptions are drawn with respect to the possible effect of options on momentum profits. It also provides a review on the impact of trading costs on momentum profits.

4.2.1 Options, information diffusion and the price efficiency of the underlying stock

Options market offers informed and/or institutional investors an alternative opportunity set to trade on their private signals. This shift towards trading in the options market is partially due to the short sales constraints, the lower transaction costs (Cox and Rubenstein, 1985) in the options market and the superiority of options as speculative tools[53]. Trading in options increases the informational efficiency of the market (Huang and Wang, 1997) and that of the underlying stock and some even argue that introducing an option affects the price of positively correlated assets to the underlying stock (Cao, 1999).

There is supporting evidence from the literature on the effect of stock options in enhancing and speeding the price discovery process. Damodaran and Lim (1991) show that following option listing prices tend to adjust more quickly to information on the underlying stock. Using a model developed by Amihud and Mendelson (1986) to decompose the return variance into components, Damodaran and Lim (1991) provide evidence of a significant increase in the price adjustment coefficient and a significant decrease in the noise variance component following option listing. Jennings and Starks

[53] John et al. (1993) show that informed traders tend to shift to the options markets as options are perceived as superior speculative tools.

(1986) find that stocks with listed options adjust faster to quarterly earnings announcements than stocks without listed options and argue that the existence of option markets improves the dissemination of earnings news. Skinner (1990) shows that the market anticipates a larger proportion of the information contained in earnings releases after option listing. This faster adjustment to earnings announcements reduces the surprise to the unexpected earnings after option listing, while Ho (1993) provides cross-sectional evidence which finds that the surprise to unexpected earnings is smaller for stocks with optioned stocks. Ho (1993) compares the optioned stock sample with 5 unilateral sub-samples based on size, higher institutional concentration, higher analyst coverage, higher trading volume and more Wall Street Index news releases. Cao (1999) presents a theoretical model that suggests a decrease in the response to public information after option introduction. He further argues that option introduction increases the incentive to acquire private information.

Moreover, there is evidence of the effect of options to resolve information asymmetry among investors. Kraus and Smith (1996) show that in the presence of heterogeneous beliefs, trading in a replicatable option reveals investors' private beliefs that results in a revealing equilibrium. Back (1993) argues that options and stocks convey different information, and as a result, the existence of options changes the information flow received in the market.

When investors execute their option trades, they reveal some of their private information which helps to resolve information asymmetry and correct mispricing. This is because options enable them to exploit some of their private information that could not be exploited otherwise. Further option trading should, therefore, reveal more information reducing arbitrage opportunities in the mispricing of the underlying stocks. Once information is revealed about the real value of the past winner and past loser stocks, it is not possible to predict the outperformance of the winner portfolio over the loser portfolio in a framework where agents are rational and trading costs are affordable. However, never has there been a direct consideration of the possibility that option trading could reduce or eliminate momentum profits, if the latter are assumed to result from underreaction to news and slow adjustment of prices.

4.2.2 The effect of Options on the characteristics of the underlying stocks

Option listing and option trading has several implications for the characteristics of the underlying stocks. The general and accepted view is that option trading increases liquidity for the underlying stocks. Shultz and Zaman (1991) and Kumar et al. (1998) show that the trading volume increases after option introduction. Cao and Ou-Yang (2009) provide empirical evidence concerning the introduction of options and its effect on the trading volume of the underlying stock. They find that trading volume increases after option introduction and that volume is always positive even when there is no change in the stock price.

Damodaran and Lim (1991) and Kumar et al. (1998) show that option trading decreases the bid-ask spread. Stein (1987) finds contrary effects of option trading on bid-ask spreads of the underlying stocks. However, Fedenia and Grammatikos (1992) suggest that highly liquid stocks tend to have spread increases after option introduction, while the opposite effect holds true for illiquid stocks.

The impact of option listing on volatility is not analogous to all stocks. There is an extensive body of literature that investigates the effect of option listing on the stock return volatility of the underlying stocks. One stream of literature finds that volatility decreases after option listing and that the underlying stocks become more stable (see, for example, Conrad, 1989; Skinner, 1989; Damodaran and Lim, 1991; and Detemple and Jorion, 1990). Detemple and Selden (1991) argue that the price of the stock increases after option listing and thus the volatility of the rate of return perceived by investors decreases. On the other hand, Grossman (1988) contends that options might increase the likelihood of destabilising the stock market as the availability of options enables investors to further their speculations in the market[54]. Furthermore, Mao and Rao (1988) show that volatile stocks become more stable after option listing because of

[54] Grossman (1988) argues that the aggregate effect of put options contracts on the underlying stock decreases its price due to price pressures. Hence, market timers find an opportunity for a potential profit when the price drops below its expected value. Particularly, he suggests that in the absence of signals about the extent to which hedging strategies are being adopted, market makers will fail to make the appropriate capital commitments in order to attempt to profit from date 2 price volatility caused by date 1 adoptions. These capital commitments must take place at date 1. Consequently, the average gain from market timing investments will reduce and the average volatility will rise.

the hedging effect while stable stocks tend to become more volatile after option listing due to the increased speculation in the options market. Not only is the literature on the impact of options on volatility inconsistent, there is some evidence showing that variations in the volatility after listing an option are not necessarily correlated to the option itself but rather to pre-listing circumstances. Particularly, Mayhew and Mihov (2004) examine the likelihood of a stock to be selected for option listing. They investigate the factors influencing the exchange in the selection process and argue that exchanges had been listing options in periods when they anticipated high volatility which explains the volatility decrease in the post listing period[55].

Given the above evidence from the literature about the characteristics for stocks with listed options, some implications can be drawn concerning the criteria used to construct a control sample and compare its momentum profits to those of the optioned stocks sample. First, option listing is shown to have a substantial improving impact on the liquidity of the stock, whereby the best neighbour non-optioned stock is one that has a high trading volume[56]. Second, based on the evidence that options help to resolve information asymmetry and reduces ambiguity of the stock value due to the high speed of price adjustment, the best neighbour non-optioned stock is one that has lower bid-ask spreads[57]. Testing the existence of momentum profits among a sample that is based on low percentage spreads investigates the assumption that momentum profits reside in stocks that are difficult to trade. And lastly, size influences the chances for option listing. As Mayhew and Mihov (2004) show, large firms have reputational capital that motivates exchanges to select for option listing. Although this effect is argued to become less effective in the 90's, the reason is that the move from single listing to

[55] Mayhew and Mihov (2004) find that option listing has no effect on volatility during 1973–1977 sub-period. However, during other periods, when the change in volatility becomes distinguishable between stocks selected for option listing and the control sample stocks, they argue that there was a shift in the exchanges' selection criteria over time seeking option listing for high volatile stocks which tends to decline afterwards. However, as they put it, it is hard to disentangle the impact of options on the volatility from the selection bias of the exchanges (for more on this, see Mayhew and Mihov (2004) p 465–469). Chau et al. (2008) investigate the impact of universal stock futures (USF) on the volatility of the underlying stock using the logit model to distinguish between stocks with and without USFs. While their paper focuses on volatility dynamics after option listing, this study aims to review the effect of options on firm-specific factors in order to identify the non-optioned stocks that have the nearest return behaviour by controlling for these factors.

[56] Especially in the recent past as Mayhew and Mihov (2004) show that there is a significant increase in the trading volume of a stock prior to its listing on the option market.

[57] Lee et al. (1993) provide evidence that firms with lower bid-ask spreads have a lower degree of information asymmetry.

multiple listing in 1990 fundamentally changed the exchange's selection process. In the UK market, however, this issue is not pertinent and the effect of size should not vanish per se. Furthermore, Lo and MacKinlay (1990b) argue that firms with large market value have a lower degree of information asymmetry. Therefore, the best neighbour non-optioned stock is one that is relatively large in market value. Size, volume and bid-ask spreads are crucial aspects of stock returns that would form a reliable benchmark for examining a sample of optioned stocks versus a control sample of non-optioned stocks.

Since listed options are shown to have an impact on the speed of price adjustment, diffusion of information, trading volume and the bid-ask spread of the underlying stocks, then short-term continuations of stock returns which are often argued to result from illiquidity or information asymmetry might be reduced or even vanish when an option is traded on the stock. In turn, momentum returns that are based exclusively on optioned stocks should also be affected if the winners and losers of the momentum strategy experience short-term continuations in stocks returns. To investigate whether momentum profits persist despite option listing, the momentum profits of both a sample of optioned stocks and a control sample should be compared. This study intends to fill that gap by investigating the effect of trading in the options market on the future returns of the winner and loser portfolios of the underlying stocks.

4.2.3 Trading costs, short sales constraints and momentum returns when options are listed

The subsections above review the literature on the informational role of options listing in the stock market and the subsequent effect of options on the underlying firm's characteristics. Speed of price adjustment, information diffusion and changes in the liquidity of the underlying stocks are also highlighted with respect to momentum returns. This subsection reviews previous studies on the robustness of momentum strategies to trading costs. It also reviews the impact of options on transaction costs in order to deduce the potential impact that options might have on momentum strategies after adjustment to trading costs.

A growing body of literature exists on the subject of transaction costs and their impact on momentum profits. Korajczyk and Sadka (2004) show that quoted and effective spread costs do not eliminate momentum profits but using a price impact measure limits the profitability of a momentum strategy after $5 billion are engaged in the strategy. Lesmond et al. (2004) argue that abnormal returns generated by momentum strategies do not exceed the trading costs associated with stocks lying in the winner and loser portfolios. Based on an equity lender institutional data, Geczy et al. (2002) find that short sale costs do not eliminate the large documented return of the loser portfolios. However, these studies do not aim to differentiate between optioned and non-optioned stocks[58].

On the other hand, the literature notes that options reduce transaction costs and mitigate the effects of short sales constraints. Figlewski and Webb (1993) show that optioned stocks exhibit a significantly higher level of short interest than stocks without options; i.e. the total number of shares in the market that have been sold short and not yet repurchased is higher for optioned stocks. They argue that in the presence of options an investor can create positive payoffs even when the expected return of the stock is negative or zero. Diamond and Verrecchia (1987) present a theoretical model which shows that trading in options reduces the costs of short selling and increases the speed of adjustment to private information, especially to bad news. Trading in options permits investors to hold positions in the options market when constraints on short sales prohibit investors from benefiting from the short selling activity. This causes option market makers to respond to the positions taken in the options market by short selling the underlying stock[59] and thus increasing the short interest as argued by Figlewski and Webb (1993). Some academics argue that the cost of trading in the options market is lower than the sequence of trades in the stock market needed to replicate the payoffs of options (Cox and Rubinstein, 1985).

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[58] Ellis and Thomas (2004) adjust momentum returns of the FTSE ALL Share 350 to trading costs that were collected from Plexis Group and that represent the average cost across all stocks traded by a fund. They report that for a full round trip of momentum trading, the average price impact costs is 0.8%; stamp duty 1%; commission costs 0.5%; spread cost 2% and short-selling costs 0.75% semi-annually. So their total trading cost estimate for a 6x6 momentum strategy is roughly 5%.

[59] Investors hold put options when they become pessimistic about the future value of a stock. The put options depress the stock price. In turn, option market makers, aware of the positions taken by the investors, they short sell the stock knowing that its price is going to drop due to the put options.

Examining the robustness of momentum profits to trading costs requires an estimation of several trading cost components. The literature identifies various costs incurred in the implementation of a momentum strategy which are: bid-ask spread component, broker's commission, immediacy costs, short sale costs and the price impact costs. However, incorporating all these components into a single trading cost measure is unattainable for several reasons. First, some data is unavailable either because it does not exist or because it is hard to obtain from brokerage institutions (such as short sale costs). Second, estimating the price impact on losers could be problematic as Korajczyk and Sadka (2004) claim that short selling involves additional costs not fully captured by their measure of price impact cost. Last but not least, there is a disagreement in the findings of prior studies on whether controlling for the price impact cost eliminates the abnormal returns from momentum strategies (Chen et al., 2002) or whether momentum profits are robust to these trading costs until $5 billions are invested into the strategy (Korajczyk and Sadka, 2004).

Firstly, since this study focuses mainly on large and liquid stocks, non-proportional (price impact) trading costs are considered trivial based on the evidence by Chen et al. (2002) that the largest decile in market value exhibits low sensitivity of price reaction to the trading volume. Given that optioned stocks are usually large cap firms, price impact costs should not severely affect the underlying stocks as pointed by Chen et al. (2002).

Secondly, there is substantial evidence verifying the real effect of short sales constraints on predictable lower stock returns. This strand of literature provides evidence that although short sale constraints exist, they are not subject to large firms. Hence, it is possible to benefit from the short selling activity after incorporating short sale costs (Geczy et al., 2002) where these costs are marginal for the largest stocks[60] (D' Avolio, 2002). Nagel (2005) argues that short sale constraints, both indirect institutional constraints and direct short-selling costs, should mainly affect stocks with low institutional ownership which are usually small cap stocks. Although high institutional ownership stocks (usually large stocks) could exhibit significant stock return predictability, Nagel (2005) argues that this predictability should not be traced to short sales constraints. Ali and Trombley (2006) show that momentum profits are largely

[60] See table 5 of D' Avolio (2002).

driven by short sale constraints that are evident in the loser portfolios of small, low turnover or "higher probability that the loan fee is relatively high" stocks. The latter variable (*Prob*) is a proxy of short sales constraints where higher probability indicates higher short sales costs[61]. They argue that the return differential between high *Prob* losers and low *Prob* losers indicates that short sales constraints are the motive for the lower returns of high *Prob* losers but not low *Prob* losers.

Given the evidence above, stocks with listed options and those within the corresponding control samples are not, as a result, subject to short sales constraints and high price impact costs. For the sake of simplicity, this study examines adjustments for trading costs which are not associated with short sales constraints or price impact. A conventional trading cost measure that is used in this study is the quoted spread measure proposed by Stoll and Whaley (1983). Direct effective spread estimates of trading costs are substantially lower than the quoted spread estimate (see for e.g. Korajczyk and Sadka, 2004; Lesmond et al. 2004), and so, it is sufficient to examine whether momentum profits exceed the quoted spread estimate of trading costs. The quoted spread estimate provides a reliable comparison with the literature on momentum profits robustness to trading costs.

It is important to note that traditional trading cost measures like the quoted spread and effective spread employ bid-ask quotes prior to the portfolio formation date in their estimates. However, the evidence from the second empirical chapter shows that losers tend to become more volatile in the ranking period than in the pre-ranking period. It was also discussed in the previous chapter that this increase in volatility is not persistent and that volatility reverses later on. *If* higher volatility has an impact on the bid-ask spreads of the stocks then consequently it *might* overestimate the cost to trade the loser stocks especially if their volatility tends to decrease over the holding period. The consideration of the spread estimate over the holding period and especially towards the liquidation date might have different implications if the spread is to vary over time.

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[61] Measuring the probability of a stock to exhibit high short sale costs is proposed by D' Avolio (2002) and used as well by Ali and Trombley (2006).

The findings from the previous chapter show that momentum profits are persistent among the weekly traded stocks sample as they are for the entire sample of stocks. Given that the trading costs of large liquid stocks are on average less than those of small thinly traded stocks, it is intriguing to examine whether trading costs would still have a significant effect on momentum returns for samples of large optioned stocks.

4.3 Research Questions and Hypotheses

There are several gaps in the literature concerning the incentives and persistence of momentum strategies that this chapter addresses. First, the well-known argument that momentum profits could result from a delay in the incorporation of information is investigated by examining the momentum profits of a sample of optioned stocks. The motivation backing this suggestion is that option trading resolves information asymmetry and improves the informational efficiency of the underlying stock. The momentum profits of optioned stocks are compared with those of control samples to draw conclusions concerning the effect of option trading on momentum profits:

Hypothesis 1: Momentum profits are reduced or eliminated as a result of option trading on the underlying stocks

Hypothesis 2: Momentum returns of optioned stocks are lower compared to momentum returns of control samples of stocks without listed options.

Momentum studies skip a month between formation and holding periods to mitigate for microstructure effects which cause reversals at short term periods before momentum profits start to occur. If trading in the options market speeds up the price adjustment to news, as argued in the finance literature, then momentum profits – *if any*– should occur at an earlier point in time. This study investigates this issue further by looking at short run weekly momentum profits.

Hypothesis 3: Short run weekly momentum strategies exhibit significant profits for optioned stocks compared to stocks without listed options controlling for size, turnover, and bid-ask percentage spread.

It is argued that momentum returns vary with respect to size, turnover and bid-ask percentage spread. These factors have various effects on information asymmetry and, in turn, on the underlying stocks. However, since option trading resolves information asymmetry and enhances the process of price discovery, then the return differential among optioned stocks regarding size, turnover and bid-ask percentage spread should be reduced or fade away.

Hypothesis 4: The differential momentum return among winner and loser stocks with respect to size, turnover and bid-ask percentage spread is not relevant in the presence of traded options.

Earlier studies examined momentum profits after adjusting for trading costs. Furthermore, some studies show that trading costs are reduced and that short-sales constraints are mitigated in the presence of traded options. Based on the findings from these studies, this chapter proposes to test the hypothesis that the reduced trading costs of optioned stocks might not eliminate the momentum profits if they exist.

Hypothesis 5: The effect that option trading has on trading costs of the underlying stocks implies that momentum profits of optioned stocks are invulnerable to trading costs.

4.4 Data and Methodology

4.4.1 Data

The data sample from which the stocks were selected is the FTSE All Share constituents. The FTSE All Share Constituents exist on DataStream as of March 2001. Historical constituent lists prior to that date were provided by FT. The sample extends from 1989 to 2007. A description of the FTSE All Share constituents is provided in the first empirical chapter. Similarly, as in the previous chapters, company names from FT historical lists are matched with DataStream. After matching the companies' names, all data variables are downloaded from DataStream using the DataStream codes for companies.

This chapter employs five different samples to test the hypotheses put forward. The first sample is the sample consisting of all stocks that belong to the FTSE All Share and that have options listed on the London International Financial Futures and Options Exchange (LIFFE). Stocks that have listed options were obtained from two sources: the DataStream and the Financial Times newspaper. The other four samples – the control samples – are constructed with respect to the control variables that are discussed in the literature review section above. But, there are some crucial aspects that need to be considered before allocating stocks into the control samples of stocks without listed options.

First, as pointed out earlier, stocks with listed options are usually large stocks which tend to be more stable than smaller stocks. Therefore, a control for size effect is required to avoid any bias arising from the cross-sectional differences between small and large stocks. Second, it is shown that more liquid stocks have different momentum returns. For instance, Lee and Swaminathan (2000) provide evidence on trading volume effects on momentum profits. In this study, turnover is used as a measure of liquidity rather than trading volume since the latter is unscaled and could be highly correlated with firm size. Therefore, the control sample should include stocks with high turnover to avoid biases arising from the volume effect. Last but not least, although most evidence assumes that bid-ask spreads tend to decline after option listing, there is supplementary evidence of the effect of trading volume on spread. More trading is shown to decrease the bid-ask spread as a result of more information awareness and less information asymmetry among various market participants[62]. Similarly, the bid-ask spread should be divided by the price to represent a scaled measure.

The control samples aim to investigate whether momentum profits disappear as a result of equity options being listed on the stock. Therefore, the stocks within the control samples are selected from the FTSE All Share stocks that do not have options

[62] See, for example, Copeland and Galai (1983) and Glosten and Milgrom (1985).

listed on LIFFE over the subsequent 6 months. The first control sample consists of the largest *n* stocks, where *n* is the number of stocks with listed options at the formation date of month *t*. The largest *n* stocks are those with the largest market value (MV) at the formation date. The second control sample consists of the *n* highest turnover stocks, where the turnover is the trading volume over the last month before the formation date divided by the number of outstanding shares at the date of formation. The third control sample has the *n* lowest bid-ask percentage spread (BAPS) stocks where the BAPS is estimated from daily data over the last month before the formation date. The last control sample consists of the *n* nearest neighbours to the stocks in the first sample with the 3 factors (MV, turnover and BAPS) considered all together. Nearest neighbours are those with the highest propensity score stocks, where the propensity score is estimated from a logit model.

The data variables are collected from DataStream International for the constituents. These include prices, MV, turnover and number of outstanding shares (weekly and monthly). Monthly (weekly) turnover is the sum of daily turnover observations over the previous month (week). Daily bid and ask prices are also collected from DataStream to estimate BAPS.

The number of stocks, *n*, in any of the five portfolios varies with respect to the number of listed stock options on LIFFE over the sample period, which tends to increase over the sample period as more options get listed over time. The maximum, minimum and mean values of *n* are 92, 47 and 73.2, respectively. Since the control samples consist of the largest, most traded or cheapest to trade, micro-structure problems resulting from infrequent trading and low priced firms are not serious, as stocks within the control samples are neither illiquid nor suffer from the low price effect. Therefore, no limitations to the selection of stocks are required as in the previous chapters, because the conditions for a stock to be among the *n* largest, *n* most traded or *n* cheapest to trade stocks indirectly control for abovementioned effects. However, it should be pointed out that some stocks are being selected among more than one control sample simultaneously. It should also be noted that when the number of stocks within the sample of optioned stocks is at the minimum of 47, the winner decile consists of 4 stocks (so does the loser decile). Furthermore, when the number of stocks within the sample of stocks with traded options reaches its maximum 92, there are only 9 stocks in either decile. Such a strategy is riskier than one where a winner or a loser portfolio is diversified among a large number of stocks, usually over 50 stocks and sometimes over 200 stocks in other studies. This is because the chances for the momentum strategy to deliver negative returns are higher since the returns of only one or 2 stocks can dramatically twist any profits around. However, the relatively small sample has an advantageous element over large samples in that it provides a more feasible and practical sample for investors to form and reduces trading costs involved in holding and short selling hundreds of stocks. The quintile formation is also applied to mitigate any potential effects arising from the examination of small samples.

4.4.2 Methodology

4.4.2.1 Constructing the samples

This section outlines the methods followed in constructing the momentum portfolios from the data samples employed in this chapter. For the sake of brevity, the sample of stocks with listed options will be referred to as "sample L"; while "sample M", "sample T", "sample B" and "sample P" refer to control samples made from largest MV, highest turnover, lowest BAPS and highest propensity score, respectively.

Sample L is formed from all stocks that are listed on FTSE All Share and that simultaneously have listed options on LIFFE for that month; the control samples are formed from all stocks that do not belong to sample L over months t to $t+6$. The MV used to construct sample M is at the beginning of month t. The turnover is estimated for all stocks within FTSE All Share that are not in sample L as follows

$$Turnover_i = \frac{\sum_{d=1}^{D} TradingVolume_{i,d}}{NumberOfShares_{i,D}} \qquad (4.1)$$

where Trading Volume$_{i,d}$ is the number of traded shares of stock i at day d, and D is the number of trading days on the LSE for the calendar month preceding the formation date. Sample B consists of the n lowest BAPS stocks, where BAPS is the daily average spread divided by the median of the bid and ask prices over month $t-1$

$$BAPS_i = \frac{1}{D}\sum_{d=1}^{D}\frac{Ask_{i,d} - Bid_{i,d}}{\left(\frac{Ask_{i,d} + Bid_{i,d}}{2}\right)} \tag{4.2}$$

where $Ask_{i,d}$ and $Bid_{i,d}$ are, respectively, the ask and bid prices and i, d and D are as before. For sample P, the propensity scores of all stocks that are within FTSE All Share but not in sample L are compared cross-sectionally at each month t. The logit model is run over all stocks of FTSE All Share at the date of formation and MV, turnover and BAPS used in the logit model are estimated as above. A value of 1 is assigned to the dependent variable if the stock has an option listed on LIFFE and a value of zero otherwise

$$Boolean(1,0)_i = \alpha_i + \beta_M (MV)_i + \beta_T (T)_i + \beta_B (BAPS)_i + \varepsilon_i \tag{4.3}$$

Where α is the intercept from the regression, and the estimated parameters β_M, β_T and β_B are the coefficients of the 3 control factors – MV, turnover and BAPS – ε is a zero-mean random residual term. The stocks with the n highest propensity scores (that were assigned a zero for the dependent variable) are then selected to form portfolio P. The logit model has been already used before by Mayhew and Mihov (2004) to address the exchanges' selection criteria for listing options; however, the explanatory variables in their model differ from the logit model in this chapter as the objective and the purpose of finding the nearest neighbours are distinct between the two studies.

This chapter also applies a weekly rebalancing methodology, in which the same procedures as above are followed to construct the data samples. Nevertheless, the weekly rebalancing methodology requires forming a new momentum portfolio at each Wednesday of week t, with the first portfolio formed on Wednesday the 3rd of January 1990 and the last portfolio formed on Wednesday the 27th of December 2006 adding up to 887 calendar formation weeks. The reason that portfolios are formed on a Wednesday is to control for the weekend effect. As above, at each week t, all stocks within any data sample are ranked according to their past j weeks' returns and held for k weeks.

To test for the impact of the control variables (MV, turnover and BAPS) within sample L, a double sorting methodology is used. Firstly, all stocks within sample L are ranked with respect to past returns and then divided into quintiles; subsequently, the top quintile is the winner portfolio and bottom quintile is the loser portfolio. Secondly, within each quintile stocks are ranked with respect to a control variable. Each quintile is then divided equally to 3 sub-quintiles resulting in a total of 15 sub-quintiles. Finally, the momentum returns of the sub-quintiles are estimated to draw implications on whether momentum portfolios generate the same profits (or losses) under the variation in the control variables.

Table 4.1 is a statistical table that exhibits the characteristics of the five samples employed in this chapter. The means (medians in brackets) of the MV, turnover and BAPS are displayed for each sample. The means from table 4.1, show that the mean MV of the sample with listed options (£Million 12008) is far larger than mean MV of any control sample (£Million 2921.44 for the first control sample). However, the sample with listed options has the lowest average turnover compared with all the control samples. It could be that the large number of outstanding shares minimises the turnover of that sample which should not have any implications on the volume traded. As for the BAPS, table 4.1 shows that stocks that have listed options are not the cheapest to trade (3rd smallest BAPS) which might support earlier evidence of option trading widening the bid-ask spreads of the underlying stocks (See Stein, 1987). Overall, it is noticed that stocks from the second sample (largest MV stocks) and fifth sample (nearest neighbours from the logit model) are more closely related to the sample with listed option than the other control samples. This raises another question of whether momentum returns can confirm the advantage of those two samples over other control samples in terms of similarity of returns, suggesting that size and the employed logit model are best at predicting a comparable control sample. Next, the following section describes the computation methods for estimating momentum returns.

Table 4.1

Characteristics of the sample of stocks with listed options and the control samples

This table reports characteristics of the sample of stocks with listed options and the control samples. The sample from which the stocks are drawn to construct the various portfolios is the FTSE All Share. At each month t, the universe of stocks is divided into 2 groups: the first group consists of all stocks with options listed on LIFFE for that month (sample of relevance); the second group contains all the remaining stocks. Four control samples are also constructed at each month t from the second group. Three control samples consist, respectively, of the n largest market value (MV) stocks, n highest turnover stocks and n smallest bid-ask percentage spread (BAPS) stocks, where n is the number of stocks within the sample of relevance at month t. The fourth control sample consists of the n highest propensity scores stocks where propensity score is estimated from a logit model that predicts the nearest n neighbour stocks to the stocks with listed options on LIFFE. In the logit model, the stocks belonging to the L portfolio are assigned a value of 1 to their dependent variables, whereas the rest of the stocks are assigned a value of zero to their dependent variables. The logit model employed regresses the dependent variable over a constant and 3 explanatory variables: MV, turnover and BAPS

$$Boolean(1,0)_i = \alpha_i + \beta_M(MV)_i + \beta_T(T)_i + \beta_B(BAPS)_i + \varepsilon_i$$

The means and (medians) of the market value, turnover and bid-ask percentage spread (BAPS) are estimated for all samples. The sample period starts on January 1990 and ends on December 2006.

	MV		Turnover		Bid-ask percentage spread	
Sample of stocks with listed options	12008.37	(11431.26)	0.118501	(0.104375)	0.009941	(0.010006)
Control Sample 1 (largest MV stocks)	2921.44	(2559.73)	0.196765	(0.09036)	0.009899	(0.009606)
Control Sample 2 (highest turnover stocks)	820.29	(829.18)	0.427911	(0.226612)	0.020292	(0.019573)
Control Sample 3 (lowest BAPS)	1875.782	(1831.116)	0.186170	(0.079175)	0.006557	(0.006397)
Control Sample 4 (highest propensity score stocks)	2463.712	(2293.865)	0.148731	(0.148231)	0.012001	(0.009597)

4.4.2.2 Computation of Momentum returns

To estimate momentum returns, stock returns are first obtained from the difference in natural logarithmic monthly prices.

$$R_{i,t} = \ln\left(P_{i,t+1}\right) - \ln\left(P_{i,t}\right) \qquad (4.4)$$

Secondly, the winner (loser) portfolio returns are determined by estimating the equally weighted average of the returns of all stocks within the winner (loser) portfolio. Finally, the return of the momentum portfolio is estimated by subtracting the losers' return from the winners' return. The methodology for constructing these portfolios over the whole sample period and the estimation of the momentum returns is illustrated below.

At each month t of the sample period a new momentum portfolio is constructed from each of the predefined samples. Stocks within any sample are ranked according to their past j months' returns and are grouped into 10 equally weighted portfolios, with those in the top (bottom) decile assigned to the winner (loser) portfolio[63]. Thus, the momentum strategy entails that a short position in loser portfolio finances a long position in the winner portfolio i.e. forming a zero-cost momentum portfolio. This position is held for k months, which results in k positions being opened at the same time. Since the first momentum portfolio in the sample period is formed on January 1990 and the last on December 2006 (although stock returns employed in this study spans over the sample period 1989 to 2007), there are a total of 204 calendar formation months in the sample period.

[63] Note that this study applies a quintile sorting as well, where winners and losers are assigned to the top and bottom quintiles. Within each table in the Results section, it is mentioned which sorting is being used. Basically, both types of formation are being employed to answer the first two hypotheses. Only the quintile formation is used in examining the third hypothesis to avoid small sample biases (more on this issue is argued in the results section dealing with that hypothesis). And eventually, only the decile formation is used when testing the last hypothesis as to examine whether trading costs can capture the largest momentum profits observed.

As in the previous empirical chapters, and in line with the literature[64], this study controls for short-run return reversals by skipping a month between the ranking period and the holding period in order to separate the momentum effect from other factors that might generate negative serial correlations[65]. In a strategy that skips a month between ranking and holding periods, stocks are ranked based on their individual returns over months $t-j$ to month $t-1$; and the holding starts at the beginning of month $t+1$. The same approach is applied for the weekly rebalanced methodology by skipping a week between ranking and holding periods. In an overlapping jxk strategy, k portfolios are held simultaneously, and the momentum return for calendar month t is the equally weighted average of k momentum portfolios

$$\overset{J\times K}{R}_{Momentum\ ,\ t,\ overlapping} = \sum_{f=t-k}^{f=t-1} \frac{R_{Winner,t,f} - R_{Loser,t,f}}{k} \quad equ(4.5)$$

where $R_{Momentum,\ t,\ overlapping}$ is the momentum return at month t; $R_{Winner,\ t,\ f}$ and $R_{Losers,\ t,\ f}$ are the mean monthly returns at month t for the corresponding winner and loser portfolios formed at month f[66].

However, an alternative way of assessing the cost to implement a momentum strategy entails embedding the transaction costs on the date of liquidation into the total trading costs. In order to estimate momentum returns after adjusting for the costs of trading, this study employs an original model for examining the persistence of momentum profits after controlling for the spread effect at the time of execution. The ranking procedure is followed as above. The holding period returns are based on quoted prices at the time of executing a buy or sell transaction. The execution time cost trading model entails that the ask price is paid for acquiring a stock and the bid price is received from selling a stock. The advantage of the execution time cost trading model over other spread based cost estimate models is that the execution time uses the quoted bid and ask prices at the dates of opening and closing positions rather than using random quoted bid

[64]See Jegadeesh and Titman (1993) who skip a week between formation and holding periods.
[65]JT (1995) show that there exist short run reversals even among large stocks which is due to overreaction to firm-specific components rather than lead-lad effects. For this reason, and in line with the previous chapter, a month is skipped between ranking and holding periods.
[66] The momentum portfolio formed at month t is not included above in equation 4.5 because the first month after formation is skipped.

and ask prices over past periods to proxy for the spread estimate. This reflects a more accurate estimate of the spread cost as it is possible for the spread of some stocks to vary over time and hence past estimates may not necessarily represent the current cost to trade the corresponding stock.

While it is possible to buy a stock at a price lower than the quoted ask price and sell at a price higher than the quoted bid price, then the proposed model introduces the strictest case of incurring the highest trading costs. In comparison with the conventional way of obtaining stock returns from the difference in logarithmic closing prices, as in equation 4.4, the execution time model replaces the ask (bid) price for the closing price if the underlying transaction was buying (selling) the stock. Recall that since, in an overlapping *jxk* methodology, there are k winner deciles held simultaneously, then the return to the winner portfolio at month t is the equally weighted average of the k positions formed through months $t-k$ to month $t-1$. The return to any of the positions opened depends on whether the portfolio has been held for k months already. If so, then it is liquidated and sold and the bid price is used to indicate the selling process. Elsewhere, the ask price that is used to buy the position is used. Therefore, the return from the long position in a winner portfolio is conditional on its formation date

$$R_{winner,\,t} = \frac{1}{k}\sum_{f=t-k}^{f=t-1}\begin{cases} n^{-1}\sum_{i=1}^{n}\left(\ln\left(Ask_{i,t,f}\right) - \ln\left(Ask_{i,t-1,f}\right) \middle| f \neq t-k, i \in winner\right) \\ \\ n^{-1}\sum_{i=1}^{n}\left(\ln\left(Bid_{i,t,f}\right) - \ln\left(Ask_{i,t-1,f}\right) \middle| f = t-k, i \in winner\right) \end{cases} \qquad equ(4.6)$$

where $Ask_{i,t,f}$ and $Bid_{i,t,f}$ are the ask and bid prices of stock i at month t that belongs to the position formed on month f, respectively; n is the number of stocks within a decile that is formed at month f. Similarly, the return from short-selling a loser stock is

$$R_{loser,\,t} = \frac{1}{k}\sum_{f=t-k}^{f=t-1}\begin{cases} n^{-1}\sum_{i=1}^{n}\left(\ln\left(Bid_{i,t,f}\right) - \ln\left(Bid_{i,t-1,f}\right) \middle| f \neq t-k, i \in loser\right) \\ \\ n^{-1}\sum_{i=1}^{n}\left(\ln\left(Ask_{i,t,f}\right) - \ln\left(Bid_{i,t-1,f}\right) \middle| f = t-k, i \in loser\right) \end{cases} \qquad equ(4.7)$$

Hence, momentum returns after adjusting for the execution time model is the difference between the winner portfolio return and loser portfolio return.

4.5 Results

Following the methods presented above this section aims to test the proposed hypotheses from the "Research Questions and Hypotheses" section in the order they are displayed. Firstly, momentum profits are assessed among the various samples and the effect of listed options is examined. Secondly, the profitability of short run strategies is investigated to see whether there exists short momentum cycles for stocks with relatively higher speed of information flow. Then, the effect of the control variables is examined over the momentum returns of the sample L, and the final subsection reveals whether momentum profits persist after adjusting for trading costs.

4.5.1 Momentum performance of stocks with listed options

Momentum profits are extensively documented in the literature and are found significant across many major markets, yet there is growing evidence which debates the practicality of putting a momentum strategy into operation or generating profits from it. For instance, the relatively higher transaction costs for short sales are negatively proportional to size (D' Avolio, 2002) and thus a momentum trader might find it difficult to implement the short selling on small illiquid stocks. To overcome this issue, the predefined sample L provides a reliable set of stocks where number of shares available for trading, availability of investors willing to lend, and relatively lower costs of borrowing facilitate the short selling procedure. Implementing momentum strategies on sample L prevails over the technical difficulties associated with short selling constraints since trading in the option market facilitates short sales. This subsection examines whether momentum profits are return anomalies that arise only from stocks that are difficult to short sell.

In the first empirical chapter evidence shows that momentum profits tend to reverse over medium horizons, which means that momentum profits are not the result of cross-sectional dispersion of unconditional means as argued by Conrad and Kaul (1998). Based on that evidence, and given also the fact that stocks with listed options incorporate information faster into their prices (for e.g. Damodaran and Lim, 1991; Figlewski and Webb, 1993; Jennings and Starks, 1986; and Skinner, 1990), this chapter focuses on testing the existence of momentum profits over short momentum cycles on the presumption that reversion in momentum returns is likely to appear sooner for samples with large and highly liquid stocks. It is also essential to note that after short selling a stock, the lender might recall it and hence shorten the life of the strategy unless the momentum trader is able to locate another lending investor willing to lend him the amount of shares to replace those being recalled. This further verifies the rationale behind using shorter momentum cycles.

Table 4.2 reports the returns to the winner and loser portfolios as well as to the momentum portfolio for 16 strategies where ranking (J) and holding (K) periods are combinations of 1, 2, 3 and 6 month horizons. The results are presented when the winner (loser) portfolio consists of the top (bottom) decile and quintile of the ranked stocks. Panel A of table 4.2 displays the results for sample L. One could say that, in general, both winner and loser portfolios generate insignificant returns most of the times. Under the quintiles formation, the winner's return is significant in only one of the 16 strategies and the loser's return is not significant in any of the 16 strategies. For the decile formation, 2 winner deciles and 6 loser deciles have significant returns out of the 16 strategies. Comparing the returns of the loser portfolios with those in the first empirical chapter for the same strategies (3x3, 3x6, 6x3, and 6x6) implies that there is a substantial disparity in the results when stocks with listed options are employed. It is crucial not to assume that any insignificant returns observed for either the winner or loser portfolios are the consequence of employing shorter momentum cycles as none of the winner portfolios seem to generate a significant positive return beyond a 2 months holding period.

However, one remarkable finding is that the decile loser portfolio that is formed on the basis of the past 6 months returns continues to obtain significant negative returns over all reported holding periods, contrary to its behaviour when j=2 or 3 months is used whereby it obtains negative but insignificant returns. Given the special characteristics for the stocks within sample L, one would expect momentum profits to disappear or at least be minimised. Bearing in mind that investors can opt to hold a position in the options market or sell short the losing stock (in other words, they can create a positive payoff even in states where an optioned stock has a negative return), there should be no opportunity for arbitrage. Therefore, what makes institutional investors or trend chasers not attempt to interfere and exploit the observed significant returns of the losers?

One possible scenario is the high transaction costs associated with trading in losing stocks. However, the monthly average return to the decile loser portfolio for the 6x6 strategy is –1.36%. Since there are 6 overlapping portfolios opened at any month in the 6x6 strategy, the transaction costs – apart from interest paid for borrowing stocks for short selling – are associated with closing one position and opening a new position. Using data from an institutional lending intermediary, D'Avolio (2002) reports a value-weighted (equal-weighted) mean loan fee of 24 (60) basis points per annum for the US market. Furthermore, D'Avolio (2002) looks at the loan fee associated with loser portfolio of a 6x6 momentum strategy and finds that the monthly average costs for short selling large, medium and small stocks are 0.27%, 0.57% and 1.05% per annum. Since sample L consists mainly of large stocks as shown in table 4.1, but on a different market (UK instead of US), the annual 0.27% (or 0.022% monthly) is too small to explain any significant return continuations of the loser portfolios.

Market underreaction, however, provides an alternative scenario for stocks with unfavourable information to continue exhibiting negative returns despite the accessibility to option trading or feasible short selling activities. It could be argued that investors' tendency to hold on to their losing stocks is causing an underreaction that is more evident on the losers' side than on the winners' side. This is in line with the suggestion by Grinblatt and Han (2005) that the disposition effect is responsible for the return continuation of losing stocks. However, the cause for such abnormal returns to be eliminated or reduced with ranking periods of 2 or 3 months and to persist among loser portfolios of 6 months ranking period is not very clear. Although option trading helps to reduce the informational inefficiency by eliminating the significant returns to the winner and loser portfolios of most strategies, there seems to be other factors which are responsible for the return continuations over short horizons of one month holding period.

Turning now to momentum profits, the results show that momentum profits persist for sample L, with the decile formation generating higher returns than the quintile formation in all cases. The decile (quintile) formation momentum strategy produces significant momentum profits in 13 (9) out of the 16 strategies employed. The most profitable strategy under the decile formation is the 6x2 strategy generating a monthly average return of 2.23% which is statistically significant at 1% level. The same strategy also earns the highest momentum profits under the quintile formation of monthly average 1.42% (statistically significant at 1% level). The most commonly assessed 6x6 strategy exhibits a monthly average of 1.84% and 1.25% under the decile and quintile formations, respectively, and are both statistically significant at the 5% level. Interestingly, the k = 6 strategy is significantly profitable regardless of the formation period being employed. Even when j is set to 1, monthly average momentum profits for k = 6 are 0.75% and 0.46% (both statistically significant at 5% level) for the decile and quintile formations, respectively. There is also an upward drift in momentum profits as j increases when k is set to 6 months. These findings imply that option trading, which is shown in the literature to facilitate shot-selling and increase the informational efficiency of the underlying stocks, cannot eliminate momentum profits that are argued to occur as a result of market frictions. The role of traded options in increasing the speed of stock price adjustments does not find strong support in the observed results as the market continues to underreact while professional market participants fail to fully eliminate momentum profits arising from this phenomenon. For instance, the two strategies 6x1 and 6x2 earn statistically significant positive returns on their winner and momentum portfolios and statistically significant negative returns on their loser portfolios. If momentum profits were attributed to slow adjustments to information, then these results have daring implications on the role of stock options as an enhancing informational tool.

The predictability of past winners to outperform past losers whereby all stocks have listed options raises doubts on whether trading in options could arbitrage price inefficiencies in the stock market. These results confirm the suggestion put forward by Grinblatt and Han (2005) that if fundamental values are unpredictable, then rational arbitrageurs cannot take infinite positions to eliminate the mispricing[67]. The persistent momentum profits suggest that the aggregate market underreaction dominates the capability of investors to arbitrage away this mispricing using stock options.

4.5.2 Momentum Performance of the Control Samples

While momentum profits persist among exceptionally large and liquid stocks that have options listed on them – although there is some evidence of partial reduction in the observed momentum profits – it is essential to examine whether the partial reduction in momentum profits is due to listed stock options or some other factors. Momentum returns of the control samples are assessed in this subsection and compared with those of sample L in order to clarify the impact of option trading on momentum returns. Although the general view is that listed options decrease the volatility of the underlying stock and enhances efficiency (for e.g. Damodaran and Lim, 1991; Detemple and Jorion, 1990; Skinner, 1989), others suggest that options might increase the stock returns volatility of the underlying stock because of increased speculation in the options market by informed investors (e.g Ma and Rao, 1988). Therefore, the extent to which stock options help in improving the informational efficiency of stock prices is further investigated through assessing the momentum profits of the control samples of non-optioned stocks and comparing them to the obtained results of sample L.

[67] De Long et al (1990) and Shleifer and Vishny (1997) point that noise trader risk might prevent arbitrageurs from attempting to correct the mispricing. Noise trader risk indicates that if the mispricing being exploited worsens in the short run, then arbitrageurs would be forced to liquidate their positions early, incurring great losses. This is because arbitrageurs are usually managing other investors' money who (the latter) force them to liquidate prematurely. Fearing the risk of facing premature liquidation, arbitrageurs hesitate to correct the mispricing.

Table 4.2

Momentum returns of optioned stocks sample and control samples

The table reports momentum profits in percentages for strategies with ranking periods j of 1,2,3 and 6 months and holding periods k of 1,2,3 and 6 months skipping one month between ranking and holding periods. Stocks in the top (bottom) decile/quintile are assigned to the Winner (Loser) portfolio. Within all portfolios, firms are equally weighted. A zero-cost momentum portfolio is formed by buying Winners and short-selling Losers. The zero-cost momentum portfolio is held for k months which allows for k positions to be opened at the same month. Momentum profit at any month is the average return from the k momentum portfolios held at that month. The sample from which the stocks are drawn to construct the various portfolios is the FTSE All Share. At each month t, the universe of stocks is divided into 2 groups: the first group consists of all stocks with options listed on LIFFE for that month; the second group contains all the remaining stocks. L represents the portfolio constructed only from the n stocks with options listed on LIFFE at month t. M, T, B and P represent portfolios formed of n stocks with largest market value (MV), highest turnover, lowest bid-ask percentage spread and highest propensity score, respectively, that don't have options listed on LIFFE at month t. MV is the market value of the stock at the formation date. The turnover is the total volume of traded shares in the month preceding the formation date divided by the number of outstanding stocks at the formation date. The bid-ask percentage spread (BAPS) is the average of the daily BAPS over the last month prior to the formation date, where the daily BAPS is the spread divided by the midpoint of the bid price and ask price. The propensity score is estimated from a logit model that predicts the nearest n neighbour stocks to the stocks with listed options on LIFFE. In the logit model, the stocks belonging to the L portfolio are assigned a value of 1 to their dependent variables, whereas the rest of the stocks are assigned a value of zero to their dependent variables. The logit model employed regresses the dependent variable over a constant and 3 explanatory variables: MV, turnover and BAPS

$$dep\,\mathrm{var}_i = \alpha_i + \beta_M (MV)_i + \beta_T (T)_i + \beta_B (BAPS)_i + \varepsilon_i$$

Finally Panel F presents the F-Test on testing the null hypothesis that the momentum profits of all samples are equal for 4 strategies: 6x1, 6x2, 6x3 and 6x6. The sample period starts on January 1990 and ends on December 2006. Newey-West auto-correlation adjusted t-statistics are used with overlapping portfolios.

Panel A: Portfolio of stocks with listed options

	K	1			2			3			6		
	J	W	L	M	W	L	M	W	L	M	W	L	M
Deciles	1	0.25	-1.39^	**1.64†**	0.05	-1.23^	**1.28***	-0.12	-0.95	**0.83^**	-0.13	-0.88	**0.75***
	2	0.19	-1.20	**1.39***	-0.04	-0.92	**0.88**	-0.10	-0.71	**0.61**	0.11	-0.89	**1.00***
	3	0.35	-1.02	**1.37^**	0.22	-0.87	**1.10**	0.30	-0.96	**1.26^**	0.36	-1.08	**1.44†**
	6	0.63^	-1.54^	**2.17***	0.63^	-1.60^	**2.23†**	0.56	-1.54^	**2.11***	0.48	-1.36^	**1.84***
Quintiles	1	0.07	-0.48	**0.55**	0.11	-0.55	**0. 66***	0.01	-0.38	**0. 39**	0.12	-0.34	**0. 46***
	2	0.37	-0.40	**0.77^**	0.16	-0.48	**0. 64**	0.09	-0.35	**0. 44**	0.26	-0.53	**0. 79***
	3	0.23	-0.39	**0.62**	0.12	-0.42	**0. 54**	0.18	-0.49	**0. 67**	0.35	-0.58	**0.93***
	6	0.53	-0.87	**1.40***	0.60^	-0.82	**1.42†**	0.57	-0.73	**1.30***	0.50	-0.75	**1.25***

Panel B: Portfolio of stocks with largest market value

	K	1			2			3			6		
	J	W	L	**M**	W	L	**M**	W	L	**M**	W	L	**M**
Deciles	1	0.55	-0.39	**0.94^**	0.29	-0.35	**0.64**	0.27	-0.28	**0.55**	0.21	-0.33	**0.54^**
	2	0.25	-0.53	**0.78**	0.24	-0.46	**0.70**	0.20	-0.33	**0.53**	0.18	-0.47	**0.65^**
	3	0.21	-0.48	**0.69**	0.23	-0.36	**0.59**	0.34	-0.37	**0.71**	0.13	-0.49	**0.62**
	6	0.65	-0.52	**1.17***	0.59	-0.43	**1.02***	0.41	-0.45	**0.86^**	0.32	-0.63	**0.95***
Quintiles	1	0.48	-0.06	**0.54^**	0.35	0.03	**0.32**	0.32	0.04	**0.28**	0.32	-0.03	**0.35^**
	2	0.43	-0.01	**0.44**	0.39	-0.05	**0.44**	0.29	0.02	**0.27**	0.34	-0.11	**0.45**
	3	0.55	-0.21	**0.76^**	0.36	-5×10^{-3}	**0.36**	0.41	-0.02	**0.43**	0.34	-0.18	**0.52^**
	6	0.52	-0.34	**0.86^**	0.50	-0.29	**0.79^**	0.49	-0.21	**0.70^**	0.48	-0.32	**0.80***

Panel C: Portfolio of stocks with highest turnover

	K	1			2			3			6		
	J	W	L	**M**	W	L	**M**	W	L	**M**	W	L	**M**
Deciles	1	0.80	-2.17†	**2.97†**	0.35	-1.90*	**2.25†**	0.04	-2.06*	**2.10†**	0.12	-1.75*	**1.87†**
	2	1.05^	-1.68*	**2.73†**	0.46	-2.07*	**2.53†**	0.24	-2.15*	**2.39†**	0.29	-1.67*	**1.96†**
	3	1.33*	-2.48†	**3.69†**	0.91	-2.50*	**3.37†**	0.76	-2.60†	**3.26†**	0.58	-2.04*	**2.53†**
	6	1.49*	-2.19*	**3.68†**	1.26*	-2.32*	**3.58†**	1.00^	-2.38*	**3.38†**	0.90^	-2.10*	**3.00†**
Quintiles	1	0.81	-0.72	**1.53†**	0.54	-0.80	**1.34†**	0.38	-0.91	**1.29†**	0.41	-0.94	**1.35†**
	2	1.01*	-0.71	**1.72†**	0.68	-1.05	**1.73†**	0.46	-1.21^	**1.67†**	0.50	-1.06	**1.56†**
	3	1.17*	-1.23^	**2.40†**	0.88	-1.43^	**2.31†**	0.73	-1.57*	**2.30†**	0.68	-1.36*	**2.04†**
	6	1.39†	-1.40*	**2.79†**	1.16*	-1.55^	**2.71†**	1.03*	-1.73*	**2.76†**	0.97*	-1.57*	**2.54†**

Panel D: Portfolio of stocks with minimal percentage spread

	K	1			2			3			6		
	J	W	L	**M**	W	L	**M**	W	L	**M**	W	L	**M**
Deciles	1	0.81*	0.62^	**0.18**	0.67^	0.39	**0.28**	0.72*	0.33	**0.38**	0.56^	0.21	**0.34**
	2	0.64^	0.26	**0.38**	0.59	0.16	**0.42**	0.61^	0.22	**0.38**	0.50	0.06	**0.44**
	3	0.59	0.28	**0.31**	0.62	0.15	**0.47**	0.76*	0.13	**0.63**	0.58^	0.02	**0.55^**
	6	0.65^	0.08	**0.57**	0.61^	-0.07	**0.68^**	0.66^	-0.03	**0.69^**	0.59^	-0.11	**0.70***
Quintiles	1	0.55	0.55	**$-7x10^{-3}$**	0.55	0.47	**0.07**	0.60^	0.46	**0.13**	0.55^	0.28	**0.26^**
	2	0.68^	0.48	**0.19**	0.58	0.41	**0.17**	0.63^	0.46	**0.17**	0.60^	0.27	**0.32**
	3	0.55	0.30	**0.24**	0.57	0.28	**0.29**	0.71*	0.28	**0.42**	0.63^	0.18	**0.44^**
	6	0.71*	0.24	**0.47**	0.72*	0.12	**0.59^**	0.76*	0.18	**0.57^**	0.68*	0.11	**0.57***

Panel E: Portfolio of stocks with highest propensity score from the Logit model

	K	1			2			3			6		
	J	W	L	**M**	W	L	**M**	W	L	**M**	W	L	**M**
Deciles	1	0.90^	-0.33	**1.23***	0.69	-0.45	**1.14***	0.73	-0.47	**1.20***	0.53	-0.40	**0.93†**
	2	0.78	-0.34	**1.13^**	0.66	-0.72	**1.39***	0.71	-0.77	**1.48***	0.62	-0.64	**1.26†**
	3	0.93^	-0.71	**1.65***	0.89^	-0.82	**1.72***	0.91*	-0.85	**1.76†**	0.58	-0.62	**1.21***
	6	1.28†	-1.13^	**2.42†**	1.26†	-1.20	**2.46†**	1.05*	-1.08	**2.13†**	0.83^	-0.88	**1.71†**
Quintiles	1	0.88*	-0.26	**1.14†**	0.65	-0.16	**0.82***	0.72^	-0.16	**0.88***	0.61	-0.12	**0.73†**
	2	0.77^	-0.13	**0.90***	0.75^	-0.20	**0.96***	0.73^	-0.17	**0.90***	0.66^	-0.16	**0.83***
	3	0.95*	-0.54	**1.49†**	0.81^	-0.49	**1.30***	0.86*	-0.39	**1.25***	0.66^	-0.31	**0.98†**
	6	1.23†	-0.82	**2.05†**	1.10†	-0.84	**1.95†**	0.99†	-0.66	**1.66†**	0.85*	-0.60	**1.45†**

Panel F: F-Test testing the equality of momentum returns of all samples

JxK	3x1	**4.11†**	3x2	**3.66†**	3x3	**3.66†**	3x6	**3.37†**
	6x1	**3.08†**	6x2	**3.41†**	6x3	**3.32†**	6x6	**2.90†**

Panel G: F-Test testing the equality of momentum returns in pairs of samples

	Sample L and Sample M		Sample L and Sample T		Sample L and Sample B		Sample L and Sample P	
JxK	2x3	**0.02**	2x3	**4.11***	2x3	**0.16**	2x3	**1.27**
	3x3	**0.54**	3x3	**4.14***	3x3	**0.80**	3x3	**0.29**
	6x3	**2.16**	6x3	**1.23**	6x3	**3.12^**	6x3	**0.00**

†, * and ^ indicates statistical significance at 1%, 5% and 10%, respectively.

4.5.2.1 Sample M:

The returns to the winner, loser and momentum portfolios of the four control samples are reported in table 4.2. Panel B reports the results for sample M (stocks with the largest market value). None of the winner and loser portfolios generate significant returns in any of the 16 strategies, though there is a tendency for winners to have positive returns and losers to have negative returns. On the other hand, the differential return between the winner and loser portfolios is significant in 7 (8) strategies out of 16 strategies for the decile (quintile) formation. Again, momentum profits seem to be occurring mainly after the 6 months ranking period. The most profitable strategy is the 6x1 and it earns 1.17% (statistically significant at 5%) and 0.86% (statistically significant at 10%) for the decile and quintile formations, respectively. Furthermore, it is noted that momentum returns of sample M do not decrease monotonically but rather exhibit a U-shaped return pattern. Thus, the largest stocks in market value that have no listed options in the options market seem to anticipate future news and adjust current prices faster than stocks that have listed options on them. This is unusual, especially given that the statistical characteristics of samples L and M in table 4.1 imply the opposite effects on momentum returns. The mean or median market value of the stocks in sample L is more than four times that of sample M. Furthermore, sample M has a larger mean turnover[68] than sample L (0.1967 and 0.1185 respectively)[69] and, according to the common view in the literature, high turnover companies should exhibit higher momentum profits (see for e.g. Lee and Swaminathan, 2000). Finally, the relative spread of the stocks within sample L exceeds by a small fraction that within sample M. So, there is no reason to believe that the difference in the percentage spread could be accountable for the disparity in momentum profits.

[68] The median turnover of sample L exceeds that of sample M, however there is not much difference as table 4.1 shows that the median turnover is 0.1043 and 0.0903 for sample L and M, respectively.

[69] The larger mean turnover of sample M than sample L does not necessarily means that the dollar trading volume is actually larger for sample M. Since sample L is 4 times larger than sample M in market value and hence firms within sample L presumably have a much larger figure of outstanding shares than firms within sample M, it is possible to assume that sample L might have a larger dollar trading volume yet a lower turnover ratio.

4.5.2.2 Sample T:

These results, however, do not hold for all control samples. Results for sample T, consisting of stocks with the highest turnover that have no listed options, are presented in panel C of table 4.2. Momentum profits of all 16 strategies are significant at the 1% level. Moreover, the magnitudes of momentum profits of sample T are relatively high reaching a monthly average of 3.68% for the 6x1 decile strategy. In particular, the 6x6 decile strategy generates a 3% monthly return compared to 1.84% for the same strategy of sample L. For all employed strategies, momentum profits in sample T are greater than their counterparts in sample L. The sample characteristics retrieved from table 4.1 show that the mean or median size (£820M or £829M) of a firm in sample T is distinct (smaller) from that of sample L (£12008M or £11431M). Nevertheless, the turnover and percentage spread are extremely larger; for instance, sample T's mean turnover is almost 4 times greater than that of sample L and sample T's mean BAPS is twice that of sample L. The obtained figures show that stocks within sample T do not fit into the same category of low trading cost stocks as stocks from sample L. One possible interpretation for the high momentum profits despite large turnover is that there exists excessive liquidity trading carried by liquidity or uninformed traders. Excessive trading by liquidity traders or trading based on public information and past price changes uninformed traders would increase the demand on the underlying winner stock and, hence, also its price. This, in turn, creates a temporary bubble that tends to burst afterwards when more liquidity traders join the cycle at a later stage (See Hong and Stein, 1999). This is noticeable as the k = 6 strategies deliver lower momentum profits than the k = 1, 2 or 3 strategies (except for 2 out of 24 cases), holding j constant; in contrast to sample L where the pattern of momentum profits from k = 1 to k = 6 takes a "U" shape in half the cases. It is also evident that uninformed trading is not present at sample L, at least to the same extent as it is within sample T, which could be attributed to the presence of option trading that facilitates mispricing corrections.

The key findings from testing sample T reveal the extent to which momentum profits could be high and potentially achievable when put into practice. The only possible drawback is that there might be high transaction costs associated with these stocks given that bid-ask spreads are generally wider for these stocks. This issue is further investigated later on in a separate subsection that deals with momentum profits after adjustments for transaction costs.

4.5.2.3 Sample B:

Most studies which examine the impact of option trading on bid ask spread find that following the introduction of options there is faster information flow and bid-ask spreads tend to reduce (e.g. Damodaran and Lim, 1991; Kumar et al, 1998; Schultz and Zaman, 1991). As a result, the underlying stocks become less costly to trade and more liquid. Sample B represents stocks without listed options which have lowest *quoted* trading costs and less heterogeneity about their intrinsic value. Next, panel D presents the results for sample B that controls for the percentage spread factor. The statistical characteristics of sample B exhibit remarkable findings in that the average percentage spread of the stocks within control sample B is substantially lower than that of sample L of listed options. The relatively low bid-ask percentage spread of sample B (0.0065) compared with other samples, including that of sample L (0.0099), suggests that informed investors should find less trading obstacles in updating their positions on stocks within sample B and that these stocks should incorporate information faster due to their higher level of liquidity. The results confirm the preliminary expectations for sample B. Momentum profits of all strategies within sample B are lower than their counterparts within sample L. Remarkably, only 4 (5) strategies out of the 16 employed strategies are significantly profitable for the decile (quintile) formation. The 6x6 strategy achieves the highest profit of 0.7% (at 5% level of significance) monthly average return for the decile formation. Likewise, the 6x2 strategy earns 0.59% (at 10% level of significance) for the quintile formation.

The smaller magnitude of momentum profits and the lesser number of profitable strategies of sample B would appear to indicate that the bid-ask percentage spread has a greater power over the listed options of stocks within sample L in anticipating future momentum profits. What is more striking than the diminishing momentum profits of sample B is the returns of its respective winner and loser portfolios. Panel D shows that the larger contribution to the momentum profits arises from the past winners' side. In fact, the returns to the past losers are mainly positive and insignificant. There is not a single loser portfolio in sample B that earns significant negative returns. On the other hand, the winner portfolios of sample B earn significant positive returns in 12 (11) out of 16 strategies for the decile (quintile) formation. This finding is very distinct from that of sample L and presents a set of stocks that anticipates information in a rather different way.

The impact of bid-ask percentage spread on momentum returns is significant and provides new empirical evidence to the literature. The evidence from this subsection shows that the bid-ask percentage spread – *as a trading obstacle* – justifies the short term return continuation of loser portfolios, although the same effect does not hold for the winner portfolios. For sample B, which has the lowest quoted trading costs, bad news is not left unexploited. Perhaps, investors are more willing to realise losses when transaction costs are low and, therefore, the losses are lower; yet, they tend to ride on losers when losses are large enough to be borne. This is further supported by the fact that sample T and sample B are correspondingly the most and least costly in terms of the observed BAPS measure and their loser portfolios earn the lowest and highest returns, respectively. The continuation of past winners within sample B to deliver significant positive returns and for past losers to deliver insignificant returns is in line with earlier literature concerning the slow response to good news but not to bad news (Hong et al., 2000).

4.5.2.4 Sample P:

Finally, the momentum returns of sample P are provided in panel E. Stocks within sample P are those that do not have listed options but have achieved the highest propensity scores from running a cross sectional logistic regression. The dummy variable represents the existence of listed options (1 for stocks with listed options and 0 otherwise) regressed over the combination of all proposed factors (i.e. MV, turnover and BAPS) and an intercept. At each month t, sample P is rebalanced with the n highest propensity scores stocks where n is the number of stocks within sample L at month t. The results show that momentum profits are present for all strategies tested using sample P. Momentum profits of sample P are more similar to those of sample L than other control samples for the decile formation. Under the quintile formation, both sample P and sample M seem to represent the best comparable control sample.

The most profitable strategy is the 6x2 strategy that earns a monthly average return of 2.46% (at 1% level of significance) and the 6x1 strategy that earns 2.05% (at 1% level of significance) for the decile and quintile formations, respectively. Similarly to what is observed in sample B, the highest propensity past winners of sample P earn significant positive returns in 8 (14) strategies out of 16 strategies. Past losers, however, earn negative returns and are all insignificant except for one strategy (6x1 decile) where the losers earn a significant negative return of -1.13% (at 10% level of significance).

The findings from sample P alongside those from sample B raise the question of why loser portfolios' future returns disappear whereas winner portfolios' future returns do not. This is contrary to the expected result that short sales constraints prevent investors from exploiting opportunities within past losers and hence significant abnormal returns should be more evident, if at all, on the losers' side. On the other hand, high turnover provides evidence of larger contribution to momentum profits from the loser portfolios which earn large significant negative returns, while size (market value), as mentioned earlier, explains the return behaviour of both past winners and losers but not of their difference (momentum profit).

4.5.2.5 Comparability of the momentum returns of the control samples

The discrete effect that the various factors (size, turnover, BAPS and listed options) have over the winner and loser portfolios suggests that the short term continuations in winners' and losers' returns are not driven by the same causes. It also suggests that momentum profits are driven by different types of underreaction which vary with stock characteristics such as size, turnover, bid-ask percentage spread, and option trading. This confirms earlier evidence of different types of momenta in stock returns documented by Gutierrez Jr. and Prinsky (2007); however, they find similar performance over the first year between momentum strategies based on raw returns and firm-specific abnormal returns whereby the former tend to reverse and the latter persist after the first year holding period.

In this study, momentum profits as well as winner and loser portfolios' returns vary with respect to the assessed factors that are used to construct the samples. Panel F shows the F-statistics of testing the similarity of momentum returns among all samples. For brevity, only eight strategies are displayed[70]. The F-statistics tests are large and significant at the 1% level, which indicates that the 5 samples (sample L and the control samples) do not exhibit the same momentum returns.

However, to test the similarity between sample L and one other control sample, panel G displays some jxk momentum strategies, namely, 2x3, 3x3 and 6x3[71]. Momentum returns of sample L are found statistically distinctive from those of sample T and sample B for some strategies. The F-statistics tests for other non-displayed strategies have no further implications for any significant distinction between sample L and either sample M or P. Yet, the value of the F-statistics tends to vary with the formation period of the momentum strategies. For instance, momentum returns between sample L and sample T are significantly different from each other for short formation periods but that difference seems to fade at the 6 months formation periods. The opposite effect holds true for the similarity of momentum returns between sample L and sample B where the observed F-statistics 0.16 is very small for the 2x3 strategy and becomes 3.12 (significant at the 10% level) for the 6x3 strategy. The reported F-statistics for distinction of momentum returns between sample L and sample M seems also to increase with the formation period but none is significant. Sample P appears to be the most comparable to sample L as it has the lowest F-statistics values[72]. The proposed logit model, as a result, provides the sample of stocks representing the nearest neighbours for stocks within sample L.

To wrap up this subsection, these findings reject the hypothesis that option trading eliminates momentum profits despite the advantages of optioned stocks on the control sample stocks to mitigate short sales constraints. It is not very clear whether stock options cannot facilitate the short selling activity or whether momentum profits are

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[70]F-statistics for the other strategies are all significant as those reported.

[71]The non-reported F-statistics show that there is no significant difference between sample L's and either sample M or P's momentum returns. What is crucial here is to report any significant difference between sample L and another control sample. The 2x3 and 6x3 strategies display evidence on significant dissimilarities. Strategy 3x3 is reported to represent how the F-statistics drift up or down.

[72]For most strategies that are not reported here.

arising from sources other than short sales constraints. This is shown through lower momentum profits in some control samples and especially in the smaller absolute insignificant returns of their loser portfolios in comparison to sample L. The smaller absolute returns of the losers for sample B than for sample L can not be attributed to the size effect as it is sample L that contains the largest market value stocks. Furthermore, while both turnover and bid-ask spread are used as measures for liquidity in the literature, they have opposite implications on momentum returns. The evidence indicates that *if* short sales constraints were the primary source for momentum profits then size and bid-ask percentage spread could restrain the impact of these constraints better than traded options. Furthermore, the logit model represents the sample of stocks representing the nearest neighbours for stocks with listed options and thus is superior to controlling for size, turnover, or bid-ask percentage spreads alone.

4.5.3 The Short run momentum returns

Based on the assumptions that traded options increase the speed of information incorporation into prices (Damodaran and Lim, 1991) and that optioned stocks respond more quickly to earnings announcements (Ho, 1993; Jennings and Starks, 1986; and Skinner, 1990), this chapter puts forward the proposition that momentum profits could occur at very short-term horizons of less than a month. To determine the fast incorporation of news into the prices of stocks, this subsection looks at the behaviour of momentum returns in response to recent news. Hence, past performance reflecting recent news is the return over the last week or 2 weeks before the formation date. The short-term holding periods examined in this subsection are 1 or 2 weeks. Starting on Wednesday the 3rd of January 1990 and ending on Wednesday the 27th of December 2006, the sample contains 887 weekly rebalanced portfolios. One week is skipped between the ranking and holding periods to mitigate for the lead-lag effect[73] which might otherwise induce negative serial correlation in stock returns.

Table 4.3 displays the returns for the weekly momentum strategies for all predefined samples using decile and quintile formations. There are 8 reported strategies

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[73] See JT (1995) and Lo and MacKinlay (1990a) for more information on the lead-lag effect.

for each sample. None of the predefined samples generate momentum profits. In fact, there is evidence of return reversals in 3 samples in support of previous studies on short-term contrarian profits. For all samples, except sample T, there seems to be a tendency for the momentum returns to decline over the second week of the holding period.

For sample L, the return to the winner portfolio is negative and the losers' return is mixed. Momentum returns are negative (i.e. contrarian profits) but they are not statistically significant. Similar results are found for sample T, with no significant momentum returns. The other 3 samples generate significantly negative momentum returns or positive contrarian profits. For instance, the 1x1 decile formation strategy of sample M earns a weekly average of -0.23% (statistically significant at the 5% level). Thus, instead, taking a long position in the loser portfolio and short-selling the winner portfolio would reverse the loss to a positive 0.23% contrarian profit or the equivalent of a monthly average of 0.92%. Contrarian profits are observed for all strategies. Control sample B earns significant contrarian profits in 3 out of the 8 strategies and generates a weekly average of 0.14% (at the 5% level of significance) for the 2x1 quintile formation. Finally, sample P earns significant contrarian profits in 5 out of 8 strategies reaching 0.24% for 1x1 decile formation strategy.

These findings suggest that momentum profits for optioned stocks do not exist at short-term horizons and that the evident return reversals indicate significant contrarian profits. These contrarian profits are attributed to either stock price overreaction to firm specific information or to the lead-lag effect whereby some stocks react with a delay to common factors or to other stocks. However, as the investigation of the sources for the documented contrarian profits are beyond the scope of this study a detailed analysis of this matter is left for future research. Since the microstructure effects are less severe among large firms or even firms with the lowest percentage spreads, these reversals could be attributed to other factors such as overreaction. Earlier evidence from the US and UK markets shows that overreaction attributes more to contrarian profits than delayed reaction to common factors or the lead-lag effect (see Antoniou et al. (2006) and JT (1995) for evidence on the UK market and the US market, respectively).

Table 4.3

Short-run Momentum Strategies of optioned stocks sample (Weekly Rebalancing)

The table reports returns in percentages to short horizons momentum strategies with ranking periods j 1and 2 weeks and holding periods k of 1 and 2 weeks skipping one week between ranking and holding periods. Stocks in the top decile (quintile) are assigned to the Winners portfolio, and those in the lowest decile (quintile) to the Losers portfolio. Within all portfolios, firms are equally weighted. A zero-cost portfolio is formed by buying Winners and selling Losers. The zero-cost momentum portfolio is held for k weeks which allows for k positions to be opened consecutively. Momentum profit at any month is the average return of the k momentum portfolios held at that week. The sample from which all the various portfolios were selected is the FTSE All Share. At each week t, the universe of stocks is divided into 2 groups: the first group consists of all stocks with options listed on LIFFE for that month; the second group contains all the remaining stocks. L represents the portfolio constructed only from the n stocks with options listed on LIFFE at week t. M, T, B and P represent portfolios formed of n stocks with largest market value (MV), highest turnover, lowest bid-ask percentage spread and highest propensity score, respectively, that don't have options listed on LIFFE at month t. MV is the market value of the stock at the formation date. The turnover is the weekly volume of traded shares divided by the number of outstanding stocks at the formation date. The bid-ask percentage spread (BAPS) is the average of the daily BAPS over the last week prior to the formation date, where the daily BAPS is the spread divided by the midpoint of the bid price and ask price. The propensity score is estimated from a logit model that predicts the nearest n neighbour stocks to the stocks with listed options on LIFFE. In the logit model, the stocks belonging to the L portfolio are assigned a value of 1 to their dependent variables, whereas the rest of the stocks are assigned a value of zero to their dependent variables. The logit model employed regresses the dependent variable over a constant and 3 explanatory variables: MV, turnover and BAPS

$$dep\,\mathrm{var}_i = \alpha_i + \beta_M (MV)_i + \beta_T (T)_i + \beta_B (BAPS)_i + \varepsilon_i$$

The sample period starts on January 1990 and ends on December 2006. Auto-correlation adjusted t-statistics are used with overlapping portfolios.

	K	Sample L			Sample M			Sample T			Sample B			Sample P		
	J	W	L	M	W	L	M	W	L	M	W	L	M	W	L	M
Deciles	1x1	-0.02	-0.01	**-0.01**	-0.17^	0.06	**-0.23***	-0.08	-0.10	**0.02**	5×10^{-3}	0.11	**-0.10**	-0.11	0.13	**-0.24^**
	1x2	-0.05	-0.02	**-0.03**	-0.10	0.07	**-0.17***	-0.14	-0.13	**-0.01**	7×10^{-3}	0.11	**-0.10**	-0.08	0.06	**-0.15**
	2x1	-0.05	-0.04	**-0.01**	-0.114	0.096	**-0.21***	-0.099	-0.15	**0.05**	0.01	0.16^	**-0.15**	-0.08	0.13	**-0.22^**
	2x2	-0.11	-0.07	**-0.04**	-0.09	0.07	**-0.16^**	-0.18	-0.10	**-0.08**	0.02	0.15^	**-0.13^**	-0.08	9×10^{-3}	**-0.09**
Quintiles	1x1	-0.04	0.03	**-0.07**	-0.09	0.09	**-0.18***	0.026	0.042	**-0.016**	0.07	0.13^	**-0.06**	-0.08	0.13	**-0.21***
	1x2	-0.04	0.01	**-0.05**	-0.07	0.08	**-0.15**†	-8×10^{-3}	0.028	**-0.03**	0.06	0.12	**-0.05**	-0.04	0.07	**-0.12***
	2x1	-0.1	0.03	**-0.13**	-0.10	0.14	**-0.24**†	-0.03	0.02	**-0.05**	0.03	0.17*	**-0.14***	-0.07	0.15	**-0.22***
	2x2	-0.1	0.01	**-0.11**	-0.07	0.14	**-0.21**†	-0.06	0.03	**-0.09**	0.04	0.16*	**-0.11***	-5×10^{-3}	0.10	**-0.10**

†, * and ^ indicates statistical significance at 1%, 5% and 10%, respectively.

4.5.4 The impact of size, turnover and percentage spread (a cross-sectional approach)

The results from the previous subsections show that while one control sample seems to generate analogous results to sample L under one test, another control sample represents a better benchmark for sample L under a different test. For example, sample P is found to be the best comparable control sample when testing monthly rebalancing overlapping momentum strategies. However, in a weekly rebalancing momentum strategy, both samples P and M earn significant contrarian profits, whereas the best neighbouring sample perceived is sample T. The changing return behaviour of the control samples with respect to sample L under various testing models raises concerns about the effects of the control variables in momentum returns. The literature has identified the relation of the underlying variables to momentum returns. This study, however, aims to investigate the role of each control variable by examining the cross-sectional difference in momentum returns of optioned stocks with respect to size, turnover and bid-ask percentage spread.

A double sorting methodology is applied by sorting stocks first into quintiles based on past returns (i.e. controlling for the momentum effect) and then sorting the quintiles according to the relevant control variable under investigation (i.e. investigating the role of each control variable in the cross-section of momentum returns). The stocks within each quintile of sample L from table 4.2 are sorted with respect to one of the control variables. Each quintile is then further divided into 3 sub-quintiles producing a total of 15 sub-quintiles as shown in table 4.4. At each month t, the double sorting methodology is applied to sample L and for a stock to be included in the assessment, it should have a valid MV, turnover or BAPS observation for that month. It is unlikely for any stock within sample L to be excluded for unavailability of data; however, when this happens, the average return of the sub-quintiles (for example, the average return of the 3 winner sub-quintiles) would slightly differ from the winner quintile return in table 4.2. Applying a double sorting methodology with the decile formation would result in few stocks within each sub-decile portfolio. For that reason, and to avoid biases arising from extremely small portfolios, the double sorting methodology is used only with the quintile formation.

Table 4.4 reports the results for the double sorting methodology for the 6x6 and the 6x3 strategies. Stocks within sample L are ranked first with respect to their past returns (6 months in this case) and then divided into quintiles. Panel A displays the sub-quintiles' returns of the 6x3 strategy after the stocks within each quintile have been ranked according to their market value in descending order prior to the second sorting. Similarly, panel B (panel C) displays sub-quintiles' returns when stocks are ranked according to turnover (BAPS) in descending (ascending) order.

In panel A, the difference in returns between the largest and the smallest firms within each quintile is not significant. Thus, controlling for past return, size does not show any significant impact on the cross-sectional difference in optioned stock returns. It is, however, noted that the difference (L-S) is positive regardless of past performance and that this difference grows negatively with past performance reaching a 1.09%[74] monthly average return dispersion between the largest and smallest loser portfolios. Panel B shows that although high turnover stocks outperform low turnover stocks – after controlling for the momentum effect – the return differential between high and low turnover stocks is only significant among past losers where H-L scores a monthly average difference of 1.21% (significant at the 5% level). The higher negative magnitude for the loser portfolios of low turnover stocks supports the disposition effect theory in that investors do not sell their losers, leading as a result to lower turnover and lower returns. Similar to the turnover effect, the BAPS has a significant effect on the cross-section of individual stock returns of past losers. Stocks with small BAPS tend to outperform large BAPS stocks once controlled for the momentum effect. Panel C shows that past losers of small percentage spreads generate a monthly average return of –0.14% while those of wide BAPS generate –1.57% (both significant at the 10% level). Yet, the differential return (S – W) is significant only for past losers where a monthly average of 1.43% is observed at the 5% level.

These findings suggest that control variables such as turnover and BAPS justify the negative return of the loser portfolios in that high turnover or small percentage spread loser portfolios are not significantly negative. While this evidence is true for optioned

[74] *t-statistic* 1.55 not reported in table 4.4

stocks, it proves that the liquidity effect on momentum profits is not exclusive to ordinary stocks[75]. The persistence of the liquidity impact on the cross-section of individual stock returns is verifiable according to the evidence provided by Avramov and Chordia (2006) on the persistence of the liquidity and momentum effect even after risk adjusting by the liquidity and momentum factors in asset pricing models. However, in this study, the impact of the control variables disappears under the 6x6 strategy. Thus, the impact of liquidity and belief asymmetry often characterized by turnover and percentage spread is temporary and does not last beyond short horizons.

Assessing the results in table 4.4 vertically, i.e. looking at momentum returns after factor adjustment, it is shown that the difference between the winners and the losers remains significant after controlling for size, turnover or BAPS. There are only two exceptions where momentum profits are not significant. The momentum return of the high turnover stocks within sample L is 0.99% (t-statistic 1.58) in the 6x3 strategy and that of medium BAPS is 0.83% (t-statistic 1.42). The momentum returns of optioned stocks are negatively correlated to size and turnover but positively correlated to percentage spreads.

The remarkable evidence here is that momentum profits decrease, rather than increase, as turnover increases when options are listed on the underlying stocks. Unlike the findings of Lee and Swaminathan (2000), this study finds that, in the presence of traded options, momentum strategies are more profitable for lower turnover stocks. However, it should be noted that lower turnover stocks generate larger momentum profits that arise mainly from the losers' side.

[75] Lee and Swaminathan (2000) provide evidence on the effect of liquidity on momentum profits and show that momentum profits are positively correlated to trading volume.

Table 4.4

The size, turnover and spread effects within momentum returns of stocks with listed options

This table shows the size effect, turnover effect and bid-ask percentage spread effect within momentum profits of stocks that have listed options on LIFFE. At each month *t*, all stocks within the FTSE All Share that have listed options on LIFFE on the date of formation of the portfolio are ranked based on their previous 6 months performance and held for *k* months. Stocks in the top quintile are assigned to the Winners portfolio, and those in the lowest quintile to the Losers portfolio. Within each quintile stocks are equally sorted into 3 sub-portfolios with respect to either their market value (MV) (descending order), turnover (descending order) or bid-ask percentage spread (ascending order). The monthly average returns for all quintiles and sub-quintiles are equally weighted. A zero-cost momentum portfolio is formed by buying Winners and short-selling Losers, skipping a month between formation and holding period. The zero-cost momentum portfolio is held for 3 (6) months which allows for 3 (6) positions to be opened at the same month in panels A, B and C (panels D, E and F). Momentum profit at any month is the average return from the *k* momentum portfolios held at that month. Newey-West auto-correlation adjusted *t*-statistics are used with overlapping portfolios. The sample period is January 1990 to December 2006.

6x3 momentum strategy

Panel A

	Large MV		Small MV	L-S
Winners	0.63^	0.51	0.60	**0.03**
Quintile 2	0.52^	0.54^	0.32	**0.20**
Quintile 3	0.51^	0.49^	0.38	**0.13**
Quintile 4	0.30	0.09	-0.07	**0.37**
Losers	-0.18	-0.62	-1.27	**1.09**
W – L	**0.81***	**1.13^**	**1.87***	**-1.06**

Panel B

	High turnover		Low turnover	H-L
Winners	0.75^	0.60^	0.37	**0.38**
Quintile 2	0.70^	0.39	0.31	**0.39**
Quintile 3	0.51	0.55	0.28	**0.23**
Quintile 4	0.20	0.20	-0.10	**0.30**
Losers	-0.24	-0.39	-1.45*	**1.21***
W – L	**0.99**	**0.99^**	**1.82†**	**-0.83**

Panel C

	Small spread		Wide spread	S-W
Winners	0.72*	0.44	0.60	**0.12**
Quintile 2	0.61*	0.41	0.36	**0.25**
Quintile 3	0.54^	0.38	0.46	**0.08**
Quintile 4	0.32	-0.06	0.06	**0.26**
Losers	-0.14	-0.39	-1.57^	**1.43***
W – L	**0.86***	**0.83**	**2.17†**	**-1.31^**

6x6 momentum strategy

Panel D

	Large MV		Small MV	L-S
Winners	0.61^	0.51	0.41	**0.20**
Quintile 2	0.52^	0.58^	0.27	**0.25**
Quintile 3	0.44	0.47	0.37	**0.07**
Quintile 4	0.25	0.09	-0.02	**0.27**
Losers	-0.40	-0.56	-1.20	**0.80**
W – L	**1.01***	**1.07^**	**1.61***	**-0.60**

Panel E

	High turnover		Low turnover	H-L
Winners	0.63	0.64	0.21	**0.41**
Quintile 2	0.64^	0.38	0.37	**0.27**
Quintile 3	0.54	0.43	0.29	**0.25**
Quintile 4	0.28	0.13	-0.08	**0.37**
Losers	-0.43	-0.55	-1.18*	**0.75**
W – L	**1.06^**	**1.18***	**1.39***	**-0.33**

Panel F

	Small spread		Wide spread	S-W
Winners	0.66*	0.49	0.38	**0.28**
Quintile 2	0.57*	0.49^	0.28	**0.28**
Quintile 3	0.50^	0.28	0.51	**-0.01**
Quintile 4	0.38	0.04	-0.07	**0.45**
Losers	-0.26	-0.47	-1.44^	**1.18**
W – L	**0.92***	**0.96^**	**1.82***	**-0.90**

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

Also evident is that the winner portfolio exhibits positive autocorrelation with significant positive returns for the largest (0.63%), highest turnover (0.75%) and smallest BAPS (0.72%) sub-quintiles. However, the same does not apply to the smallest, lowest turnover or widest BAPS sub-quintiles. It is contrary to the expectations about the autocorrelations in stock returns as improved price discovery arising from additional trading and lower BAPS should decrease return autocorrelations. Campbell et al. (1993) show in their model that stock return autocorrelations decline with trading volume. Llorente et al. (2002) show that returns generated by investors' hedging trades are serially negatively correlated for large stocks or low bid-ask stocks (where information asymmetry is less severe and speculative trading is trivial). They also find that current volume is negatively associated with future returns. Furthermore, it has been shown that there is a negative and significant cross-sectional relationship between turnover and average stock returns, Chordia et al. (2001). This study, however, finds support from evidence of higher trading volume increasing individual stock return autocorrelation by Säfvenblad (1997) who finds that autocorrelation becomes significantly stronger after high trading volume. The finding implies that while high turnover winners (and also the second winning high turnover quintile) experience significant autocorrelation and low turnover winners do not, the autocorrelation is attributed to profit taking; i.e. investors sell off their shares after a significant increase in price to lock in their gains or to realise profits. While this selling activity might temporarily depress prices after investors sell their stocks to realise gains, prices would rise again afterwards. This implies that the overall movement of the price is trending upward.

4.5.5 Fama-French adjusted momentum returns

In this subsection, the returns of the momentum portfolios are adjusted to the Fama-French three factor (FF3F) model. In the first empirical chapter, CAPM and FF3F models were applied on the event time momentum returns to adjust for risk factors. The results show that risk-adjusted momentum profits do not disappear over the medium horizon for both models. Since, both models gave similar findings, then it suffices here to use only the FF3F model as a check for robustness given its ubiquity in empirical finance. Equation 2.5 from the chapter 2 is applied on the five samples and for all strategies as in table 4.2.

Table 4.5 reports the obtained alphas (intercepts) from the FF3F regression with their statistical inferences. Panel A of table 4.5 shows that momentum profits of sample L are reduced substantially – both in terms of the magnitude of the returns and the number of profitable strategies – after risk adjustments., The number of strategies delivering significant momentum profits are 13 (9) for the decile (quintile) formation before risk adjustment compared with 9 (6) significantly profitable momentum strategies after risk adjustments. Furthermore, the momentum returns are mainly significant for strategies with 6 months ranking period or 6 months holding period. For the decile formation, momentum profits persist among nine strategies reaching a 1.56% monthly average return (significant at the 5% level) for the 6x2 strategy. Although there is a substantial decrease in momentum returns, the FF3F is unable to fully explain the momentum effect, at least for the decile formation. This finding that the FF3F has been unable to explain short-term return continuations even for a restricted sample where stocks are tremendously large confirms earlier evidence on the failure of the FF3F to capture the momentum effect.

If the Fama-French model has a consistent impact on all control samples as on sample L, then one could argue that a fraction of the momentum profits arising from large and liquid stocks in these samples is due to risk premiums. To examine that issue, the risk adjusted momentum returns of the control samples are obtained and displayed in panel B through panel E of table 4.5. The momentum profits for sample M (largest MV) disappear largely after risk adjustments for both the decile and quintile formations. On the contrary, all strategies continue to generate positive significant returns for sample T after risk adjustments. The raw momentum profits of all strategies are larger than the reported alphas from the FF3F model for both decile and quintile formations of sample T. While it is generally acceptable to say that momentum returns tend to reduce after risk adjustments, the ability of an asset pricing model to explain the returns of one sample but not the other suggests that there could be a missing risk factor that could encompasses the short-term return continuations. As Fama and Fench (1996) state that the short-term return "*continuation anomaly exposes one of its (the model) shortcomings*" (p. 82).

The suggestion above is further confirmed from the results of samples B and P. The FF3F model seems to reduce or partially explain the momentum returns of one sample more than another. Risk adjusted momentum profits are significant in only one strategy in sample B (for both decile and quintile formations), whereas they seem to persist in sample P. In particular, the most profitable strategy yields a monthly average risk-adjusted return of 2.30% and 2.01% (both significant at the 1% level) for the decile and quintile formations, respectively. On the other hand, the reported alphas are insignificant and small for strategies with short formation and holding periods within sample B. Panel D shows that the alpha for the 1x1 momentum strategy is negative, though insignificant. This substantiates previous evidence of the existence of contrarian profits over very short-term horizons (Antoniou et al., 2006 and JT, 1995).

The overall evidence from the risk adjusted momentum returns indicates that although the FF3F is unable to fully explain momentum profits, it is, nonetheless, found to reduce momentum profits on average. It is also shown that the effectiveness of the abovementioned model varies with respect to stock or sample characteristics. Momentum profits disappear largely after risk adjustment within samples M and B; yet their strong persistence within the sample T implies that justification for these high returns might be addressed by a missing risk factor from the FF3F model.

To this point, it has been shown that stock options, as an enhancing informational tool, do not eliminate momentum profits. This evidence is strengthened by showing that for some control samples, momentum profits appear to reduce more than optioned stocks after risk adjustment. While risk adjustment can not explain the anomaly, turnover and percentage spread appear to explain partially the momentum profits arising from the loser's side. This brings attention to the issue of whether trading costs are the primary reason for market participants not being able to exploit these profits.

Table 4.5

Fama-French alphas for momentum returns of special liquefiable portfolios (Monthly Rebalancing)

This table reports the alphas (intercepts) in percentages after adjusting momentum profits for the Fama-French three factor model for strategies with ranking periods j of 1,2,3 and 6 months and holding periods k of 1,2,3 and 6 months skipping one month between ranking and holding periods. Stocks in the top (bottom) decile/quintile are assigned to the Winner (Loser) portfolio. Within all portfolios, firms are equally weighted. A zero-cost momentum portfolio is formed by buying Winners and short-selling Losers. The zero-cost momentum portfolio is held for k months which allows for k positions to be opened at the same month. Momentum profit at any month is the average return from the k momentum portfolios held at that month. The sample from which the stocks are drawn to construct the various portfolios is the FTSE All Share. At each month t, the universe of stocks is divided into 2 groups: the first group consists of all stocks with options listed on LIFFE for that month; the second group contains all the remaining stocks. L represents the portfolio constructed only from the n stocks with options listed on LIFFE at month t. M, T, B and P represent portfolios formed of n stocks with largest market value (MV), highest turnover, lowest bid-ask percentage spread and highest propensity score, respectively, that don't have options listed on LIFFE at month t. MV is the market value of the stock at the formation date. The turnover is the total volume of traded shares in the month preceding the formation date divided by the number of outstanding stocks at the formation date. The bid-ask percentage spread (BAPS) is the average of the daily BAPS over the last month prior to the formation date, where the daily BAPS is the spread divided by the midpoint of the bid price and ask price. The propensity score is estimated from a logit model that predicts the nearest n neighbour stocks to the stocks with listed options on LIFFE. In the logit model, the stocks belonging to the L portfolio are assigned a value of 1 to their dependent variables, whereas the rest of the stocks are assigned a value of zero to their dependent variables. The logit model employed regresses the dependent variable over a constant and 3 explanatory variables: MV, turnover and BAPS

$$dep\,\mathrm{var}_i = \alpha_i + \beta_M (MV)_i + \beta_T (T)_i + \beta_B (BAPS)_i + \varepsilon_i$$

The sample period starts on January 1990 and ends on December 2006. Newey-West auto-correlation adjusted t-statistics are used with overlapping portfolios.

	Decile				Quintile			
J	$k=1$	$k=2$	$k=3$	$k=6$	$k=1$	$k=2$	$k=3$	$k=6$
				Panel A: Sample L				
1	1.35*	1.05*	0.53	0.47	0.48	0.54	0.21	0.30
2	1.18^	0.53	0.26	0.69^	0.62	$4\text{x}10^{-3}$	0.21	0.55^
3	0.91	0.60	0.77	1.02^	0.27	0.16	0.30	0.61^
6	1.46^	1.56*	1.50^	1.34^	0.94*	0.99^	0.90^	0.90^
				Panel B: Sample M				
1	0.93	0.60	0.52	0.46	0.55	0.28	0.25	0.31
2	0.70	0.63	0.45	0.56	0.37	0.35	0.20	0.36
3	0.59	0.48	0.60	0.50	0.66	0.26	0.35	0.41
6	1.06^	0.88^	0.77	0.87^	0.70	0.65	0.58	0.69^
				Panel C: Sample T				
1	2.95†	2.11†	1.89†	1.76†	1.45†	1.18†	1.10†	1.18†
2	2.61†	2.30†	2.16†	1.81†	1.56†	1.50†	1.47†	1.39†
3	3.28†	2.93†	3.00†	2.45†	2.16†	2.03†	2.02†	1.85†
6	3.47†	3.25†	3.14†	2.86†	2.54†	2.39†	2.47†	2.30†
				Panel D: Sample B				
1	$1\text{x}10^{-3}$	0.26	0.33	0.30	-0.01	0.03	0.10	0.22
2	0.26	0.32	0.25	0.31	0.13	0.10	0.11	0.25
3	0.18	0.31	0.46	0.42	0.12	0.14	0.28	0.34
6	0.30	0.47	0.52	0.59^	0.30	0.47	0.49	0.51^
				Panel E: Sample P				
1	1.34^	1.15^	1.19*	0.86†	1.19*	0.83*	0.89*	0.30
2	1.01	1.26^	1.37*	1.15*	0.84	0.90^	0.84^	0.76*
3	1.53^	1.61*	1.60*	1.10*	1.42*	1.23*	1.17*	0.90*
6	2.30†	2.29†	1.98†	1.60†	2.01†	1.89†	1.59†	1.41†

†, * and ^ indicates statistical significance at 1%, 5% and 10%, respectively.

4.5.6 The robustness of momentum returns to trading costs

This study follows a different approach in estimating the quoted spread than that in the literature. Since momentum returns are the consequence of the near past performance, the quoted spread estimate should as well reflect the trading cost in the near past from the formation date. Based on the evidence that momentum returns reverse beyond medium horizons, bid ask spread characteristics associated with the winner or loser stocks could therefore change over the life cycle of a momentum strategy. Measuring the quoted spread with observations dating back 12 months might, therefore, undermine the real costs associated in trading the top and bottom decile stocks. This study is based on observations over the last month to estimate the quoted spread which is necessarily similar to the BAPS estimate since the quoted spread follows the same criterion as the bid ask percentage spread (i.e. the ratio of the bid ask spread and the bid ask midpoint). The quoted spread estimate or the quoted percentage spread is a reliable comparison to the existing literature on momentum profits and trading costs.

Furthermore, this study proposes a new estimate of trading costs based on the quoted prices at the execution dates of portfolio formation and portfolio liquidation as provided by equations 4.6 and 4.7. The new model is tested and the results are discussed after the quoted spread estimate below. But first, this study assess the profitability of momentum strategies by adjusting profits to the estimate of Ellis and Thomas (2004) (see subsection 4.2.3 above). Their estimate of the one-round trip trading costs of a 6x6 momentum strategy is roughly 5%, and the monthly momentum profits of the 6x6 strategy for sample L is 1.84% (11.04% in 6 months), therefore, profits after adjusting to these costs are 6.04% over six months or 1% monthly. For the 6x2 and 6x3 strategies, the observed momentum profits are even higher and the costs become smaller as the interest of short-selling cost reduces with shorter holding periods.

Table 4.6 reports the robustness of the momentum strategy to the quoted spread estimate for all samples. Holding the ranking period J constant, the quoted spread estimate should not change as the holding period K changes. This is because the quoted spread is based on costs up to the formation date. For instance, the average quoted bid ask spread over the whole sample period with $J = 1$ is 1.53% and 2.16% for the winner and loser portfolios of sample L (panel F), respectively. Thus, the estimated 1.53% is subtracted from the return of all winner portfolios of the strategies 1x1, 1x2, 1x3 and 1x6. Since the return for the loser portfolio is deducted from that of the winner's to obtain the momentum return, the quoted spread estimate is added to the loser's return rather than subtracted. It is important to notice that a positive return by the loser portfolio indicates the amount of losses incurred in short selling the losing portfolio after trading costs are embedded. In other words, the return to the momentum strategy at any month is then

$$\sum_{r=1}^{n}\left(R_{r,w}-Q_{r,w}\right)-\sum_{s=1}^{n}\left(R_{s,l}+Q_{s,l}\right) \qquad (4.8)$$

Where $R_{r,w}$ is the return to the winner portfolio; $R_{s,l}$ is the return to the loser portfolio; and $Q_{r,w}$ and $Q_{s,l}$ are the quoted spread estimates of the individual stocks r and s, respectively. In panel A of table 4.6, the winner portfolio under the 3x3 strategy of the sample L generates a monthly average of –0.99% and the loser portfolio generates a monthly average loss of 1.37%. This is totalled to a monthly average of –2.36%.

As table 4.6 shows, there is not any single profitable momentum strategy in any of the samples after adjusting for the quoted spread trading cost. All momentum returns are found significantly negative after adjustment for the quoted spread estimate except for 4 out of 80 strategies (of all samples together) that were found negative but not significant. This suggests that momentum strategies deliver significant losses if the quoted bid ask spread estimate employed in this study reflects the real costs for trading. Compared with existing literature on momentum profits and transaction costs, Korajczyk and Sadka (2004) show that momentum profits are robust to the quoted bid ask spread and Lesmond et al. (2004) find that momentum profits disappear for the quintile of largest stocks but not for the quintile of highest turnover[76]. This suggests that

[76] Lesmond et al (2004) use the direct effective spread estimate + commission estimate. The sum of the direct effective spread estimate + commission estimate is shown to be close to the quoted spread estimate when both models were applied to the whole sample of stocks.

the impact of trading costs on the momentum strategies applied on the US market is less than that of the UK market.

Sample T appears to incur the maximum losses (panel C) whereas sample B incurs the least losses (panel D). However, prior to adjusting for trading costs, sample T and sample B generate the maximum and minimum momentum profits, respectively (see table 4.2). This implies that the larger momentum profits are correlated with larger trading costs, and that once these trading costs are incorporated into momentum returns, stocks that gain most start to lose most. In fact, this is apparent across the different samples in panel F of table 4.6 where the quoted spread estimates of sample T are the highest and those of sample B are the lowest. Panel F also shows that the quoted spread estimates of the loser portfolios are much larger than those of the winner portfolios for three samples (samples L, T and P). Not surprisingly, these three samples deliver the highest momentum profits before adjusting for trading costs. The conclusion from these results is that the larger contribution to momentum profits arising from the losers' side is accompanied with larger (up to twice in some cases) trading costs for the loser stocks than for the winners.

The initial inference this outcome has about relative strength strategies is that momentum profits are not robust to trading costs, specifically in relation to the quoted spread estimate. There could be more than one reason why the momentum returns estimated in table 4.6 are much lower for than those estimated by US studies. Firstly, the quoted spread is estimated using the closing quotes of only the last month prior to the formation date where spreads might get wider[77]. Lesmond et al. (2004) use closing quotes from 18 months to 6 months prior to formation date. However, Korajczyk and Sadka (2004) use the half-quoted spread estimate. Secondly, it might be the case that trading costs on the LSE are relatively higher than those on the US exchanges[78].

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[77] The finding from the previous empirical chapter that stock return volatility tends to increase as time approaches formation date for the loser portfolios suggests that their spreads may tend to increase as well.
[78] Easley et al. (1996) argue that the LSE is less liquid than the NYSE as some stocks might not trade for weeks in the latter market but one stock never traded for 11 years in the former market. Infrequent trading is often attributed to high trading costs.

Table 4.6

Momentum Profits after adjusting for the quoted spread estimate

The table reports momentum profits in percentages for strategies with ranking periods *j* of 1,2,3 and 6 months and holding periods *k* of 1,2,3 and 6 months skipping one month between ranking and holding periods after adjusting for trading costs using the quoted bid-ask spread measure. Stocks in the top decile are assigned to the Winners portfolio, and those in the lowest decile to the Losers portfolio. Within all portfolios, firms are equally weighted. A zero-cost momentum portfolio is formed by buying Winners and short-selling Losers. The quoted bid ask spread is estimated for each individual stock and then subtracted from the stock's return if the stock belongs to the winner portfolio, or added to the stock's return if the stock belongs to the loser portfolio. The zero-cost momentum portfolio is held for *k* months which allows for *k* positions to be opened at the same month. Momentum profit at any month is the average return from the *k* momentum portfolios held at that month. The sample from which the stocks are drawn to construct the various portfolios is the FTSE All Share. Samples L, M, T, B and P are as defined before. The sample period starts on January 1990 and ends on December 2006. Newey-West auto-correlation adjusted *t*-statistics are used with overlapping portfolios.

Panel A: Portfolio of stocks with listed options

	K		1			2			3			6	
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-1.28*	0.78	**-2.06†**	-1.48†	0.93	**-2.41†**	-1.66†	1.20	**-2.86†**	-1.67†	1.27^	**-2.94†**
	2	-0.93^	0.98	**-1.91†**	-1.17*	1.26^	**-2.43†**	-1.23†	1.47*	**-2.70†**	-1.01*	1.30^	**-2.31†**
Deciles	3	-0.93^	1.31	**-2.24†**	-1.06*	1.45^	**-2.52†**	-0.99*	1.37^	**-2.36†**	-0.92*	1.25^	**-2.18†**
	6	-0.42	1.08	**-1.50**	-0.42	1.02	**-1.44**	-0.48	1.08	**-1.56^**	-0.57	1.26	**-1.83***

Panel B: Portfolio of stocks with largest MV

	K		1			2			3			6	
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-0.60	0.77	**-1.37†**	-0.86^	0.81^	**-1.68†**	-0.88^	0.88^	**1.76†**	-0.94*	0.83^	**-1.77†**
	2	-0.83	0.66	**-1.49***	-0.84	0.73	**-1.57†**	-0.88	0.86	**-1.74†**	-0.90	0.72	**-1.62†**
Deciles	3	-0.86	0.71	**-1.57***	-0.84	0.84	**-1.68***	-0.73	0.82	**-1.55†**	-0.94*	0.70	**-1.64†**
	6	-0.45	0.69	**-1.14^**	-0.51	0.78	**-1.29***	-0.68	0.77	**-1.45†**	-0.77^	0.58	**-1.35†**

Panel C: Portfolio of stocks with highest turnover

	K		1			2			3			6	
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-1.47*	0.98	**-2.45†**	-1.93†	1.25	**-3.18†**	-2.24†	1.09	**-3.33†**	-2.16†	1.39*	**-3.55†**
	2	-1.02^	2.34†	**-3.36†**	-1.61†	1.95*	**-3.56†**	-1.83†	1.87*	**-3.70†**	-1.78†	2.35†	**-4.13†**
Deciles	3	-0.57	1.81^	**-2.38***	-0.99^	1.79^	**-2.78†**	-1.13*	1.69^	**-2.82†**	-1.31*	2.25†	**-3.56†**
	6	-0.24	2.46*	**-2.70†**	-0.48	2.32*	**-2.80†**	-0.74	2.26*	**-3.00†**	-0.83	2.55†	**-3.38†**

Panel D: Portfolio of stocks with lowest BAPS

	K	1			2			3			6		
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	0.15	1.28†	**-1.13†**	0.02	1.05†	**-1.03†**	0.06	0.99†	**-0.93†**	-0.10	0.87*	**-0.97†**
	2	$-8x10^{-3}$	0.92*	**-0.93***	-0.06	0.82*	**-0.89***	-0.04	0.89	**-0.93†**	-0.15	0.73	**-0.88†**
Deciles	3	-0.05	0.96*	**-1.01***	-0.02	0.82^	**-0.84***	0.12	0.80^	**-0.68^**	-0.07	0.69^	**-0.76***
	6	$5x10^{-3}$	0.75^	**-0.74^**	-0.03	0.60	**-0.63^**	0.01	0.63	**-0.62**	-0.06	0.55	**-0.61^**

Panel E: Portfolio of stocks with the highest propensity score

	K	1			2			3			6		
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-0.43	1.37	**-1.80†**	-0.64	1.24*	**-1.88†**	-0.59	1.23*	**-1.82†**	-0.79	1.26†	**-2.05†**
	2	-0.45	1.79†	**-2.24†**	-0.57	1.41†	**-1.98†**	-0.53	1.36†	**-1.89†**	-0.61	1.47†	**-2.08†**
Deciles	3	-0.24	1.47*	**-1.72†**	-0.29	1.36*	**-1.65†**	-0.27	1.34*	**-1.61†**	-0.60	1.53†	**-2.13†**
	6	0.21	1.16*	**-0.94**	0.19	1.10*	**-0.91^**	-0.02	1.22*	**-1.24***	-0.25	1.40†	**-1.65†**

Panel F: quoted spread costs of winner and loser portfolios

	Sample L		Sample M		Sample T		Sample B		Sample P	
J	W	L	W	L	W	L	W	L	W	L
1	1.5375	2.1662	1.1553	1.1639	2.2837	3.1482	0.6577	0.6603	1.3351	1.6988
2	1.1268	2.1842	1.0867	1.193	2.0682	4.0267	0.6571	0.6638	1.2424	2.1349
3	1.2886	2.3338	1.0703	1.1965	1.9007	4.2953	0.6542	0.6672	1.1867	2.1875
6	1.0476	2.628	1.0964	1.2171	1.7381	4.6519	0.6513	0.6673	1.0714	2.3023

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

An alternative way of measuring trading costs is by using the closing bid-ask quotes at the dates of execution. This proposed model – bid-ask quotes at execution time (BAQET) – captures trading costs over the holding period up to the date of liquidation of portfolio. Equations 4.6 and 4.7 above, describe the methodology of estimating momentum profits after adjusting for the BAQET model. Essentially, the BAQET model reflects the transaction costs such as the spread cost and broker's commission cost at both the date of formation and the date of liquidation. Furthermore, buying only at the ask price and selling only at the bid price should certainly encompass immediacy costs involved in instant updating of positions held.

Table 4.7 reports the winner, loser and momentum returns for all samples and for 16 various ranking and holding periods. For all samples, and regardless of the ranking period, momentum returns are significantly negative (at the 1% or the 5% level of significance) when the momentum portfolio is held for only one month (k = 1). As the holding period increases (K > 1), momentum profits increase gradually until they become significantly positive under the 3x6 and 6x6 strategies for both sample L and sample T. The momentum profits of sample L for the 3x6 and 6x6 strategies are 1.08% and 1.55% (both significant at the 10% level), respectively. The momentum profits of sample T for the same strategies are 1.67% and 2.08% (both significant at the 5% level), respectively. On the other hand, sample M and sample B incur the least losses at the beginning of the holding period and earn insignificant low returns at the end of the holding period when other samples tend to perform sufficiently well. Sample P does not generate any significant momentum profits as its 6x6 strategy earns a monthly average of 0.83% (with a t-statistic 1.52).

The findings from table 4.7 have appealing implications for the behaviour of the bid-ask spreads of the winner and loser portfolios over the holding period. These implications suggest that the actual momentum profits are best reflected in the width of the spread rather than closing prices. To clarify this issue further, the following example is given.

The momentum returns of sample L before and after adjusting for the BAQET model are compared for two strategies: 6x3 and 6x6. Table 4.2 panel A shows that the monthly average loser returns for the 6x3 and 6x6 strategies are –1.54% (or –4.62% 3 months cumulative return) and –1.36% (or –8.16% 6 months cumulative return), respectively. This means that when the holding period k is extended from 3 to 6 months, the cumulative return of the loser portfolio decreases by 3.54%. Thus, the cumulative return for the first 3 months of the holding period is –4.62% and that for following 3 months of the holding period is –3.54%. While it seems more profitable to liquidate the portfolio at k = 3 and invest in a new position that generates more profits at shorter horizons, the story from the bid and ask quotes suggests otherwise. Table 4.7 panel A shows that short selling the loser stocks at the bid price and buying it back at the ask price generates a monthly average return of –0.72% (–2.16% cumulative return) and –1.11% (–6.66% cumulative return) for the 6x3 and 6x6 strategies, respectively. The cumulative return during months 4 to 6 of the holding period is –4.5% compared with only –2.16% in the former 3 months. Therefore, although there was a greater price decline in the first 3 months, momentum strategies require that they are held for a longer period to compensate for the relatively wider bid-ask quotes at the early stages of the momentum cycle.

The momentum returns after adjusting for the BAQET model reveals the drawbacks of the previous quoted spread trading cost estimate. While the quoted spread model generally represents the average costs associated with each individual stock, it misrepresents the profitability of the momentum strategy as it overlooks the variation in the width of the bid-ask spread throughout the holding period and it assumes the same fixed amount of cost regardless of the holding period. Thus, the 6x3 strategy would still look more attractive than the 6x6 strategy after adjusting for the quoted spread estimate because the same fixed costs are deducted from both strategies.

The quoted spread estimate of trading costs is found to overestimate the trading costs as it considers the spread estimates at the formation period and ignores those at the liquidation period. Consequently, it does not distinguish among the more profitable strategies since bid and ask prices beyond the formation date and the potential contraction of the spread over the holding period are overlooked. In addition, the quoted spread estimate does not distinguish between the more profitable sample data as it shows in table 4.6 that sample L tends to outperform sample P (its nearest neighbour) most of the times, however, when adjusting for the BAQET model only sample L out of the two samples earns significant profits.

Table 4.7

Momentum profits after adjusting for the Bid-Ask quotes at execution time cost model

The table reports momentum profits in percentages for strategies with ranking periods *j* of 1,2,3 and 6 months and holding periods *k* of 1,2,3 and 6 months skipping one month between ranking and holding periods using the Bid and Ask prices at the date of executing the order. Stocks in the top (bottom) decile are assigned to the Winner (loser) portfolio. Within all portfolios, firms are equally weighted. A zero-cost momentum portfolio is formed by buying Winners and short-selling Losers. The price to buy (short sell) Winners (Losers) at the beginning of the holding period is the Daily Closing Ask (Bid) price, whereas the price to sell (buy) Winners (Losers) at the end of the holding period is the Daily Closing Bid (Ask) price at that day of liquidation. If there was no trading in the market on the first day of the month then the nearest trading day is used to replace the non-trading day starting with the next trading day. The zero-cost momentum portfolio is held for *k* months which allows for *k* positions to be opened at the same month. Momentum profit at any month is the average return from the *k* momentum portfolios held at that month. The sample from which the stocks are drawn to construct the various portfolios is the FTSE All Share. Samples L, M, T, B and P are as defined before. The sample period starts on January 1990 and ends on December 2006. Newey-West autocorrelation adjusted *t*-statistics are used with overlapping portfolios.

Panel A: Sample L

	K		1			2			3			6	
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-1.22*	0.71	**-1.93†**	-0.67	-0.24	**-0.43**	-0.59	-0.35	**-0.23**	-0.39	-0.65	**0.26**
	2	-1.03*	1.25^	**-2.29†**	-0.66	0.20	**-0.87**	-0.39	-0.03	**-0.36**	6×10^{-3}	-0.63	**0.64**
Deciles	3	-0.87	1.23	**-2.11†**	-0.33	0.20	**-0.53**	-0.01	-0.25	**0.23**	0.26	-0.81	**1.08^**
	6	-0.45	1.18	**-1.64***	0.24	-0.27	**0.51**	0.39	-0.72	**1.11**	0.43	-1.11	**1.55^**

Panel B: Sample M

	K		1			2			3			6	
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-0.52	0.86	**-1.39†**	-0.22	0.32	**-0.55**	-0.03	0.26	**-0.30**	0.08	-0.08	**0.17**
	2	-0.87	0.68	**-1.56†**	-0.31	0.25	**-0.57**	-0.12	0.16	**-0.29**	0.04	-0.26	**0.31**
Deciles	3	-0.84	0.88	**-1.72***	-0.25	0.33	**-0.58**	0.07	0.12	**-0.05**	-6×10^{-5}	-0.28	**0.28**
	6	-0.43	0.83	**-1.27***	0.13	0.27	**-0.13**	0.14	-7×10^{-3}	**0.14**	0.23	-0.41	**0.64**

Panel C: Sample T

	K		1			2			3			6	
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-1.48*	1.95†	**-3.43†**	-0.79	0.18	**-0.97**	-0.76	-0.56	**-0.20**	-0.31	-1.07	**0.76**
	2	-1.19^	2.69†	**-3.89†**	-0.49	0.25	**-0.74**	-0.37	-0.55	**0.17**	-0.06	-0.92	**0.86**
Deciles	3	-0.65	2.33†	**-2.99†**	0.04	-0.10	**0.15**	0.25	-0.89	**1.14**	0.40	-1.27	**1.67***
	6	-0.17	2.7†	**-2.91†**	0.41	0.23	**0.18**	0.49	-0.77	**1.26**	0.68	-1.39	**2.08***

Panel D: Sample B

	K	1			2			3			6		
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-0.12	1.48†	**-1.61†**	0.19	0.84*	**-0.64^**	0.42	0.62^	**-0.19**	0.40	0.37	**0.02**
	2	-0.22	1.13	**-1.35†**	0.15	0.63	**-0.48**	0.32	0.53	**-0.20**	0.35	0.22	**0.13**
Deciles	3	-0.20	1.18†	**-1.39†**	0.26	0.64	**-0.38**	0.52	0.43	**0.08**	0.43	0.17	**0.26**
	6	-0.21	0.94*	**-1.16†**	0.17	0.37	**-0.20**	0.37	0.24	**0.13**	0.48	$6x10^{-3}$	**0.47**

Panel E: Sample P

	K	1			2			3			6		
	J	W	L	M	W	L	M	W	L	M	W	L	M
	1	-0.78	2.01†	**-2.79†**	-0.10	0.79	**-0.89^**	0.29	0.37	**-0.08**	0.28	0.10	**0.17**
	2	-0.63	2.35†	**-2.99†**	-0.08	0.63	**-0.71**	0.28	0.17	**0.10**	0.40	-0.14	**0.55**
Deciles	3	-0.41	2.30†	**-2.71†**	0.23	0.69	**-0.45**	0.53	0.12	**0.41**	0.43	-0.18	**0.62**
	6	0.08	2.04†	**-1.96†**	0.67	0.40	**0.27**	0.69^	$-2x10^{-3}$	**0.69**	0.64	-0.19	**0.83**

The subscripts †, *, and ^ denote statistical significance at 1%, 5%, and 10% respectively

Momentum profits disappear totally after adjustment to the quoted spread measure of trading costs. Moreover, the samples that generate higher momentum profits before adjusting to trading costs are found to generate lower returns after adjustments. An alternative trading cost measure – Bid-Ask Quotes at Execution Time – is proposed that takes into consideration the variation in the width of the spread over the holding period of the strategy. The BAQET model estimates trading costs at the formation and liquidation dates of the portfolio. The results show that momentum profits persist for samples L and T after adjusting for the BAQET estimate. The findings are intriguing in terms of the challenge that they present to previous evidence on trading costs and momentum returns. However, the disparity in the results after adjusting to each trading cost model and the lack of correspondence between the two measures suggest that the BAQET model should be tested on other samples representing various countries where momentum profits are shown to disappear after adjustment to formation period bid-ask quotes.

4.6 Conclusion

This chapter puts forward several issues that are not yet addressed or clarified in the finance literature. Based on extensive studies concerning the impact of options on the underlying stocks, this chapter integrates the findings of these studies to investigate the effect of options on the most puzzling equity anomaly: the momentum effect.

Underreaction to news, short-sales constraints preventing investors from creating payoffs with negative states, or high transaction costs due to heterogeneous beliefs about the value of the security are all agued to maintain momentum profits. There is evidence that options increase the speed of price adjustment to news such as earnings (Damodaran and Lim, 1991; Ho, 1993; Jennings and Starks, 1986; Skinner, 1990). Diamond and Verrecchia (1987) and Figlewski and Webb (1993) show that option trading mitigates short sales constraints and there are also previous studies that suggest that option trading resolves information asymmetry and reduces heterogeneity among investors as sophisticated and institutional investors reveal some of their private information through their option trading (Kraus and Smith, 1996). In light of these findings, momentum profits are examined among optioned stocks to see whether they persist despite the argued effects of options on the underlying stocks.

The results show that momentum profits persist among a sample of optioned stocks for the sample period 1990 – 2007. Since an investigation of the impact of options on speed of price adjustment, short selling activity or information asymmetry is beyond the scope of this chapter, the major conclusion that momentum profits continue to exist suggests two possible scenarios: that high transaction costs are responsible for unexploited momentum profits and/or that aggregate market underreaction of liquidity traders dominates the capability of informed traders to arbitrage away this mispricing using stock options.

Comparing these results to four control samples constructed from the largest firms, highest turnover firms, lowest bid-ask percentage spread firms and highest propensity score firms[79] confirms the suggestion of Gutierrez Jr. and Prinsky (2007) that there are different types of momenta though this study attributes these different types to factors such as market value (MV), turnover and bid-ask percentage spreads (BAPS). Furthermore, samples M and B generate less momentum profits and higher loser returns than sample L. This raises concerns of whether options do not in fact reduce short sale costs or whether momentum profits are due to factors such as underreaction to news which are resolved faster within non-optioned stocks of lower BAPS and large MV. This issue requires further investigation to disentangle the sources of momentum from the impacts of options on the underlying stocks, and is left for future research.

To test whether options' ability to increase the speed of price adjustment is reflected in short-run weekly momentum strategies, momentum profits are examined at one and 2 weeks (ranking and holding periods) horizons. The results show that reversals rather than return continuation are evident at the short-run weekly horizons for sample L and the control samples. These reversals generate significant contrarian profits within samples M, B and P. Since microstructure effects are less severe among large firms or

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[79] The propensity score is estimated from a logit model that predicts the nearest n neighbour stocks to the stocks with listed options on LIFFE (with respect to size, turnover and bid-ask percentage spread) where n is the number of optioned stocks at month t.

even firms with the lowest percentage spreads, these reversals could be attributed to other factors such as overreaction as documented in the previous literature.

Next, the chapter looks at the possible sources of momentum profits by investigating the cross-sectional effects of MV, turnover and BAPS on the momentum returns of sample L. There is empirical evidence that turnover and BAPS have a significant cross-sectional effect on the momentum returns of the loser portfolios but not the winner portfolios. Additionally, the results show that winners with large MV, high turnover and low BAPS generate significant positive returns. The positive autocorrelation in high turnover rather than low turnover stocks is attributed to profit taking and confirms earlier evidence by Säfvenblad (1997). The Fama-French 3 factor model partially reduces momentum profits of sample L and the control samples. The resulted alphas from FF3F model are lower than the raw momentum return. However, samples L, T and P continue to have several significant profitable momentum profits after risk adjustment. In comparison with the results from the first empirical chapter, the reported FF3F alphas of the samples in this chapter are relatively reduced. These findings are interpreted as the FF3F have a stronger capability of capturing the risk of large and liquid stocks and that a missing factor might explain the abnormal returns in smaller and less liquid stocks.

Finally, this chapter addresses the question of whether trading costs could prevent investors from exploiting the observed momentum profits among all samples employed in this study. Two measures for trading costs are applied: the quoted spread and a new measure that depends on the bid-ask quotes at the portfolio formation and liquidation execution dates. The BAQET estimate reveals several drawbacks of the previous quoted spread trading cost estimate. First, the quoted spread model suggests the same costs for strategies with similar ranking periods but different holding periods as it does not capture the variations in quotes over the holding period that the BAQET does. Second, a momentum strategy with a shorter holding period might seem more profitable when profits are estimated with closing prices. However, the BAQET estimate shows that although there might be larger price movements in the shorter horizons, the momentum strategy would perform better when held longer as the variations in bid and ask quotes imply much lower costs at later periods. The variations in the quotes of the stocks over the holding period need further investigation which is left for future research. This chapter concludes that there is a bid-ask quote variation over time in the winner and loser portfolios and that a new trading cost estimate that controls for such variation has been employed and can not explain the momentum profits of optioned stocks or those mostly traded non-optioned stocks.

5 Chapter Five: Conclusion

The results for the main research questions that are raised in the empirical chapters are summarised in this chapter. Afterwards the implications of the findings are discussed and possible areas of research in relation to momentum studies and other finance topics are highlighted.

5.1 Summary of findings and conclusions

This thesis has undertaken a wide and detailed investigation of momentum strategies which had added to our understanding of this important issue. There are two key issues that remain disputable among researchers. This thesis attempts to clarify relevant aspects to these two issues. The predictability of future abnormal returns challenges the EMH and form the first dispute among financial economists and academic researchers. On the other hand, the sources of momentum returns and the incentives for the short-term continuations in stocks returns reveal difference in opinions.

While this thesis does not aim to test the EMH, it aims to examine whether momentum is driven by market frictions, investors' behavioural biases or both as mentioned in Chapter 1. Therefore, this study attempts to control for every identified trading obstacle that is argued to induce momentum profits. In doing so, this study examines whether market frictions are entirely responsible for the observed momentum profits. To control for market frictions, this thesis has controlled for small, illiquid and low priced stocks which are expensive to trade and whose information is difficult to obtain. The thesis also controls for the bid-ask bounce effect. Furthermore, to ensure that none of the stocks might be suffering from information ambiguity, the thesis considers a sample of optioned stocks, where these stocks are argued to suffer the least from information asymmetry. One further important aspect that is related to market frictions is the trading costs associated in forming and liquidating the momentum portfolios. These aspects are transformed into empirical tests that are undertaken throughout the empirical chapters to provide further evidence to the existing literature on the predictability of future abnormal returns and its challenge to the EMH. The thesis finds supporting evidence to theories suggesting market underreaction to news which could be possibly explained by biases in investors' behaviour.

The second issue of relative importance to momentum is understanding the sources of momentum profits and identifying which stocks experience larger return magnitudes during the short-term return continuations. If some stocks are found to underreact further to public news than other stocks, then momentum strategies could be more profitable if they were designed to take into consideration the specifications of these stocks. While some studies show that firm-specific components affect the cross-sectional dispersion in momentum returns, other studies provide evidence of the impact of industry or other market wide information on momentum returns. While both arguments are supported by numerous studies, this thesis attempts to understand the role that each factor has on past winner and past loser stocks. The effect of the firm-specific components is more prevalent on the losers' side, whereas the industry effect is limited to the winners' side. The thesis also provides evidence of the effect of several firm-specific components on the cross-section of momentum returns in chapters 3 and 4. The methods used and the major findings from the empirical chapters are summarised below.

Chapter 2 establishes the continuous presence of momentum profits for the particular and more recent sample period employed here for the FTSE All Share Index constituents. Considering the extant literature, chapter 2 controls for the proposed explanations for the performance of such strategies, such as the low price firm effect, thin trading, and the IPO effect. The chapter employs both non-overlapping and overlapping methodologies for 16 different strategies.

According to the evidence, momentum strategies deliver significant profits after the controls and under both methodologies for all strategies. Losers earn significant negative returns that are larger in magnitude than those of winners. This implies that profits of the momentum strategies employed are mainly driven by the short position in losers. This last point may have implications for cases where short selling is prohibited or difficult due to the market conditions and/or the instruments available for such positions to be taken. Nonetheless, the losers' significant returns are not permanent as can be seen by the event time methodology where reversals beyond 11 months post formation indicate that losers revert winners. The reversal of momentum returns in the postholding period is compatible with the findings of JT (2001) and confirms their critique of Conrad and Kaul's (1998) findings that momentum profits are driven by the unconditional risk in individual stocks. The findings also confirms JT's (2002) findings that autocorrelation primarily induces momentum profits.

Controlling for the possibility of seasonality driving the results, the chapter finds that momentum returns are sensitive to seasonality; however, the empirical evidence from this study contradicts earlier UK evidence on momentum and seasonality. Momentum profits reverse in April but not in January after the 1998 tax reform. The findings support earlier studies on tax-loss selling activity and its association with individual traders in the US market. Another important issue is that the UK tax-loss selling disappears for institutional investors but not for individual investors despite modifications applied to the new Tax Act. However, what represents new evidence to this field of research is that individual investors are continuing their tax-loss selling activities by extending the period between selling and repurchasing the losing stocks over one month. The reason is that the counter bed-and-breakfasting law states that the minimum permitted period for repurchasing a declared losing stock is one month in order to claim losses from that stock. This finding is supported by the observed insignificant negative momentum returns in the adjacent months March and May.

The selection of the particular market and period was made with an important consideration that allows assessing the effects that changes in market microstructure would have on the speed of information incorporation and hence momentum profits. The results show that momentum profits are present both before and after the introduction of the fully automated electronic auction system in the LSE. However, when the sample is partitioned to study whether more recent momentum performance reflects the same pattern of other anomalies that have experienced decreased performance or elimination after discovery, the results show that although momentum profits persist in the recent time window, the momentum profitable investment cycle has shortened. More specifically, ranking stocks on the past 9 and 12 months does not generate momentum profits, whereas for ranking periods below that momentum profits are present up to a 6 month window and not 9 or 12 month as usual in the literature.

Perhaps this finding indicates that momentum is slowly moving towards the same direction of elimination as other anomalies due to possibly gradual awareness. Alternatively, it could be argued to be the result that the market performance and its relationship to momentum for the more recent times. However, the evidence shows that market states do not affect momentum, contrary to other markets such as the US. More specifically, falling markets do not affect momentum negatively as would be expected, but positively as momentum profits are on average higher following down markets. Nonetheless, market states appear to have an impact on the post-holding periods (specifically year 2 and 3 after formation). Hence the chapter concludes that the market is becoming gradually aware of the existence of momentum profits. The fact that some momentum strategies continue to be profitable over a 6 months holding period could signal that either rational arbitrageurs are not detecting potential profits for at least the first 6 months, or they do so, but they are unable to eliminate them until accumulated profits become rewarding (and larger than trading costs: borrowing costs, information and research costs, transaction costs etc).

Chapter 3 investigates sources of momentum profits and provides further clarifications on the role of market-wide and firm-specific information in momentum returns. This study takes into account the impact that liquidity might have on stock returns, when weighing the effects of market-wide and firm-specific components. The results show that momentum profits are significant for three liquidity samples that vary from illiquid to very liquid. This provides key evidence to the UK literature on momentum as it shows that momentum profits are not associated to illiquid stocks that are not traded frequently. It further hints at the role of trading costs in preventing arbitrage, specifically for weekly traded stocks that are found profitable up to 6 months. In other words, the findings cast doubts about the effect of trading costs when winner stocks that have been trading at least once a week over the past 26 weeks continue to outperform loser alike stocks.

Stock return volatility has been shown in earlier studies that it has a significant impact on the cross-sectional dispersion in momentum returns. Furthermore, the components of volatility encompass both macro and micro news and thus represent an appropriate factor to examine the raised issue. When the volatility of each of the winner and loser portfolios is estimated, the evidence is that losers are significantly more volatile than winners in all three samples for both measures of volatility: the standard deviation of weekly returns and a Garman-Klass High-Low-Open-Close historical price estimate. Thus, the higher volatility of the losers is not due to a concentration in illiquid stocks. Thus, the higher volatility of the losers is not due to the illiquidity effect. Another interesting finding is that loser portfolio's volatility increases as time approaches the formation date. The increase in volatility prior to the formation date for losers only, but not for winners, indicates that the former tend to become riskier after experiencing a period of bad performance during the ranking period. The overall findings from these results imply that loser behaviour is different from that of winner prior to formation date and irrespective of the liquidity level. These conclusions are further affirmed by the examination of the impact of volatility on the cross-section of momentum returns.

A distinctive contribution of this chapter and thesis is in assessing the role of market-wide versus firm-specific factors in the cross-section of momentum returns. A newly proposed model for adjusting stock volatility to industry volatility is employed, which entails that the stock's σ is regressed against that of its industry's and the sum of squares of the residual term represents the adjusted volatility estimate. The results show that both market-wide and the firm-specific factors have a significant impact on the cross-section of momentum returns, confirming earlier findings in the literature. However, the new evidence in this study is that the impact of each factor varies with the level of liquidity as well as with the past performance of the individual stocks. While the cross-section in losers' returns is mainly driven by idiosyncratic volatility, that of the winners' returns is attributed to industry volatility instead. However, the role of industry volatility in the winners' cross-sectional returns increases with liquidity level; in other words, it becomes more effective and dominant in highly liquid weekly traded stocks. The findings suggest that winners and losers are not driven by the same factors, and while momentum profits persist in various liquidity level samples, the industry effect is present for highly liquid stocks only. The chapter deduces that since losers contribute more to momentum profits, and since the sources of their large magnitude is attributed to firm-specific components (idiosyncratic volatility), industry does not seem to be a major source for the cross-section of momentum returns in individual stock-based momentum, despite its noticed effect on highly liquid winners.

Chapter 4 examines momentum strategies on optioned stocks in the UK market over the sample period 1990–2007. The motivation is to examine whether momentum profits relate only to stocks that suffer from relative ambiguity or is due to slow incorporation of news into stock prices. Since it is argued that options increase the price efficiency of the underlying stock and since they increase the market awareness about the value of the underlying stock, then momentum profits should not exist for the optioned stocks sample if the market is efficient. The issue of whether or not momentum profits occur is put forward into investigation and the results are compared with 4 control samples of non-optioned stocks for 16 strategies based on the combination of 1, 2, 3 and 6 months ranking and holding periods. The findings show that, for all samples, there are significant momentum profits, but not for all tested strategies. A control sample with the lowest bid-ask spread earns the least, while a control sample with the highest turnover earns the most. This implies that low bid-ask spread can facilitate the incorporation of news into prices more efficiently than excessive trading. Furthermore, while both turnover and bid-ask spreads are interchangeably used as proxies for liquidity in the literature, they have opposite implications on momentum returns. Moreover, losers' returns are higher for control samples with larger market value stocks and lowest bid-ask percentage than optioned stocks. This finding comes at odds with the expectation that the optioned loser stocks should least experience short-term continuation in stock returns. Thus, the role of options as an enhancing tool for reducing short sales costs and constraints is questioned as is their role in minimising heterogeneity across market traders.

Next, chapter 4 looks at weekly momentum strategies based on the combination of 1 and 2 weeks ranking and holding periods. The assessment of short-run momentum strategies examines the effect of option trading on momentum returns over a very short-term period after formation. The motivation for this test is that option trading is argued to speed the incorporation of news into prices and to overcome micro structure effects that are more severe in smaller stocks, and therefore, there should be no reversals in momentum returns at the very short-term for optioned stocks. The empirical results show that reversals are significant for some control samples, whereas insignificant returns are generated by optioned stocks. The obtained reversals are argued to be the result of a short-term overreaction rather than of micro structure effects. The chapter, also, looks at the impact of the control variables on the cross-sectional momentum returns of optioned stocks. Results show that bid-ask percentage spread and turnover have a significant impact on the cross-section of losers' returns. The observed upward trend of high turnover winners points to the presence of profit taking activity, whereas low turnover winners do not experience the same significant upward trend.

Trading costs might explain why momentum profits are larger for optioned than for non-optioned stocks and why optioned losers earn lower returns than non-optioned losers. This finding contradicts the expectation that it should be more feasible to exploit the expected returns of optioned loser portfolios since they are subject to less short sales constraints. If trading costs cannot provide sufficient evidence for that, then the results should lead to one of two conclusions: the first is that options fail to reveal information, and in fact increase ambiguity about the value of the firm and increase heterogeneity among market traders; the second is that informed traders or arbitrageurs are reluctant to exploit their signals fearing excessive noise trading that is facilitated by trading in options and undertaken by liquidity or naïve traders. However, the second conclusion indicates that the aggregate underreaction of irrational traders dominates the potential attempts of arbitrageurs even for optioned stocks.

The results from testing the robustness of momentum profits to the quoted spread estimate (percentage spread) show that momentum returns do not exceed the incurred costs. In fact, all samples and all strategies generate significant negative momentum returns after adjusting for the quoted spread estimate and the supreme profitable sample (non-optioned highest turnover stocks) becomes the sample with the largest losses after adjusting for the quoted spread estimate. However, the evidence from testing the robustness of momentum profits on a newly proposed model that is based on the Bid-Ask Quotes at the Execution Time (BAQET) of forming and liquidating the portfolios reveals different findings. Optioned stocks and a sample of non-optioned highest turnover stocks show that trading costs cannot fully explain momentum profits. While the latter sample tends to generate the highest losses in the quoted spread estimate, it generates significant momentum profits under the BAQET model estimate. These findings indicate the importance of the methodologies and the assumptions followed in estimating trading costs and reveal some of the drawbacks of the quoted spread trading cost estimate in particular and traditional measures that follow similar routes in estimating the cost of trading. The advantageous performance of the BAQET model estimate could also be useful in estimating trading costs for other trading strategies or in the wider financial research. The robustness of momentum profits to the BAQET trading cost estimate indicates that underreaction exists even among stocks that do not suffer from information ambiguity or severe market frictions.

First, this thesis implements momentum strategies on a distinctive data set and finds appealing and original evidence of market gradual awareness towards momentum profits. Then the thesis examines firm-specific and market-wide effects on momentum returns and the variations of these effects with respect to the liquidity of the firm. The thesis also shows evidence that market underreaction to news exists even among optioned stocks and stocks with the least information uncertainty, least exposed to market frictions and that while trading costs reduce momentum profits, they do not eliminate them entirely.

5.2 Implications for future research:

This section aims at raising future research questions on critical concerns that are brought to light through the new empirical evidence shown in this thesis. The implementation of new methods and techniques and the employment of a distinctive and recent data sample have revealed further details corresponding to momentum strategies in particular and to the finance literature in general. This section addresses four points that are potential areas for further investigation and shows how the resolving of these issues could provide additional insights for understanding the behaviour of stock returns.

- More research is needed in order to examine the behaviour of losing stocks over the extended March-April-May period by ascertaining the institutional versus individual percentage ownership of these losing stocks. The research will need to identify the type of investors engaging in the selling and repurchasing of losing stocks that tend to experience longer negative returns. The results would show whether the counter bed and breakfasting law (1998 Tax Act) has managed to minimise the attempts of tax-avoidance and what procedures the government should undertake to end such activities.

- Firm-specific volatility plays a major role in the cross-section of losers' returns, which is more prevalent than in the winners' returns. Further research is required to understand the reasons that make losers become highly volatile as the formation date approaches while winners do not. Since the larger contribution of momentum returns stems from the losers' side and since the cross-sectional variation between high volatility and low volatility stocks is significant and wide enough among losers, then understanding how the volatility builds up might help in explaining why losers tend to become riskier after experiencing a period of low returns.

- Another matter that is uncovered through the findings of this thesis is the ability of the methodology chosen to estimate trading costs to capture the time-varying changes in the bid-ask spread. Chapter 4 shows that the control sample that is most profitable after adjusting using one method suffers the greatest losses after adjusting using the other model. Moreover, chapter 4 finds that using closing prices is distinct from using bid and ask quotes, in that some momentum strategies which are most profitable when returns are estimated with closing prices lose their chief position when performance is estimated with respect to bid and ask quotes. To this extent, it is important to examine the robustness of momentum profits against the BAQET on data samples from other markets, specifically the US market. It is also important to examine the robustness of various trading strategies to the BAQET model before irrevocable inferences are drawn about the profitability of these strategies.

- The time variation in the width of the spread should also be investigated to see whether there is a consistent behavioural trend for the spread of the losers and winners over the formation and holding periods. As chapter 3 shows that the volatility of the loser portfolios tends to increase towards the formation date, it would be expected that the spreads also become wider during higher volatile periods. If this is the case – that spreads tend to widen and later on narrow – then market traders should anticipate the future width of the spread and act upon it. Failing to do so, would suggest that market traders are myopic in the way they perceive future expectations of even the most frequently traded stocks and optioned stocks. This assumption is based on findings from chapter 4 that bid and ask quotes at early stages of the holding period do not signify any potential profits, however as the bid-ask spread tend to narrow in due course, potential momentum profits begin to occur.

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